Analysing Nursing Workload in Intensive Care Unit by Using a Novel Objective Tracking System

by Peng Guo

A thesis submitted for the degree of

Doctor of Philosophy in

Mechanical Engineering

at the

University of Canterbury

Christchurch, New Zealand

October 2015

Acknowledgement

I would like to thank my supervisor, Distinguished Prof. J. Geoffrey Chase, who responsibly provides me plenty of support. Thank you for giving me continuous guide and direction to my research. Thanks for your positive response to my requests and paper writings. You let me know what research is and how to conduct one. You let me dare to question, to challenge, and to create. Your support makes me feel confident that I can achieve this academic goal.

Many thanks also go to my Co. supervisor Dr. Geoff Shaw. Thanks for all your help in making this research possible in the Christchurch Hospital ICU. You give me the opportunity to experience the clinical ICU and work there. We both know how difficult every step is to make this experiment actually happen. Thank you for always encouraging me and supporting me for every achievement I made.

I also would like to thank my assist supervisor, Dr. Yeong Shiong Chiew, who becomes a good mentor and friend to me. Thank you for giving me continuous ideas and possible solutions to many specific problems I encountered. Your conscientious researching attitude let me understand the right attitude in academic field.

I must also thank all those people who give me technical support to solve all specific problems. Many thanks go to Dr. Richard Green, Dr. Adrian Clark, and Dr. Lei Shao, who helped me with Kinect coding; to Dr. Chris Pretty, Dr. Paul Docherty, and Dr. Matt Signal, who helped me with Matlab coding, statistic analysing, and paper writing; and to Dr. Jennifer Dickson and Dr. Liam Fisk, who helped me with thesis writing and Android coding.

I also need to thank many ICU staff, especially nurses Danny, Joyce, Jamma, Hannah, Gabriel, and Shelly, who helped participating and cooperating in this research. Your supporting attitude makes this research feasible and accurate. Many of you are so supportive that you help me understand the ICU working environment, explain nursing duties to me, and share your nursing experience.

Many thanks also go to my colleagues in bio-engineering centre. You guys create an awesome, positive, and enjoyable working environment. Thanks are given to Azlan, Salwa, Shunny, Musa, Cong Zhou, Fatanah, Jackie, Ummu, Sam, Hina, Alex, and Reza.

I also would like to thank all my friends in New Zealand, Jeremy, Esther, Miao Liu, Nathan, Bradley, Jun, Connor, Paul and many others. You guys enrich my life and open my world in the past few years. A big thank you also goes to my girlfriend Lisha Niu, who encourages and supports me at all time.

I must also thank China Scholarship Council and University of Canterbury Joint Scholarship, who provide me funds to make this research possible.

Last but not least, I would like to thank my parents and my family. Without your support and your understanding, I would not have stood a chance to accomplish this study. I owe you many thanks and apologies.

Table of Contents

List of Figures

List of Tables

Abstract

Quantifying nursing workload in Intensive Care Unit (ICU) can help optimize nursing resources, allowing allocation of nurses according to patient demand. This can benefit the ICU patients and nurses through the provision of adequate nursing care, prevention of nurse burnout, and reducing of ICU fixed costs. However, quantifying nursing workload is extremely challenging. Current nursing workload assessment tools, such as the therapeutic interventions scoring system (TISS) and nursing activities score (NAS), are subjective and laborious, requiring experienced nurses and researchers to fill out forms. Therefore, an automatic system that can objectively quantify nursing workload is required. The development of computer imaging and tracking technology offer possible solutions to track nursing activities.

This research focuses on developing a novel tracking system that can continuously track bedside nursing interventions and quantify nursing workload. Nursing workload is then compared with patient clinical data to analyse which factors strongly influence patient nursing demands. The first part of this thesis discusses the development of a tracking system, and the second part discusses the correlation between quantified nursing workload and patient clinical conditions.

Facial detection, color detection, infrared detection, and local position measurement (LPM) are the 4 possible approaches to continuously track nurse bedside interventions. These 4 approaches are evaluated, and infrared detection was the optimal non-invasive approach that most suited implementation in the Christchurch Hospital ICU environment.

A clinical activities tracking system (CATS) was developed to track bedside nursing interventions continuously. The CATS hardware contains a Microsoft Kinect with image and infrared depth sensors, controlled by a portable laptop. The CATS software was designed under Microsoft Express C++ environment, implementing OpenNI and OpenCV libraries. The Kinect sensor is placed onto the ceiling to monitor a defined detection area. When an object enters the detection area, it is converted into an unidentifiable unrecognizable blob to protect privacy, and its location over time is recorded.

CATS was tested in an experimental environment using two metrics, distance and dwell time to quantify nurse-patient interaction. CATS was then implemented in the Christchurch Hospital ICU. A trained ICU researcher performed manual observations on nursing workload at the bedside and compared with data collected using CATS. The researcher calculated the direct nursing intervention time for each observed hour for 30 hours. The observed direct nursing intervention time was then compared to CATS recorded nursing intervention time. It was found that the CATS recorded nursing intervention is highly correlated with manual observed intervention, and thus CATS was able to record nursing intervention objectively. A preliminary study shows that nursing intervention density is higher during the day compared to night time.

Clinical trials include all patients admitted and allocated to a monitored bed between 04/08/2014 to 03/05/2015. 23 patients, with a total of 104 patient days, were recorded. Patient demographics, various patient acuity assessment scores, and workload assessment scores, including APACHE-II, APACHE-III, SAPS-II, SOFA, TISS-28, and NEMS, were calculated and compared with nursing intervention recorded by CATS. The patient's sedation level, as

quantified by GCS, RASS, and sedation drug dose, were also assessed and compared with the nursing intervention recorded by CATS.

In this study, APACHE-III and SAPS-II were found to have better resolution in describing patient acuity compared to APACHE-II and SOFA. Both TISS-28 and NEMS display poor sensitivity to different patient specific nursing demands because only 36% of TISS-28 score varies from patient to patient. Equally, no significant trend was found between nursing intervention and sedative dose or sedation level assessed by GCS or RASS. Results showed that the nursing intervention is highly patient-specific and conventional generalised approaches were not able to capture the specificity. CATS was able to capture specificity automatically and objectively.

Overall, the objective nursing intervention tracking system provides an objective approach to automatically quantify nursing intervention. This system is validated in clinical trials, indicating its high accuracy and robustness. Nursing intervention captured by CATS shows that during the day nursing intensity is higher than at night time. In addition, none of patient sedation level, acuity level, TISS-28, NEMS, age, length of stay, admission type, or intubation condition shows a strong clinical correlation with nursing time. The difficulty of quantifying nursing intervention using conventional scores revealed a need for an objective system to evaluate nursing workload. At this stage, it is almost impossible to link nursing invention assessed directly by CATS to any existing assessment system based on tasks, patient severity or similar clinical data. As a result, CATS has the potential to standardise nursing workload quantification objectively, and is much less invasive and labor intensive than current assessment systems and scoring based approaches.

Abbreviations

ABL: Arterial blood line

AIDS: Acquired immunodeficiency syndrome

ANZICS: Australian and New Zealand Intensive Care Society

APACHE: Acute physiology and chronic health evaluation

APE: Absolute percentage error

API: Application Programming Interface

APS: Acute physiology score

A_{time}: Actual manually observed

B-NMDS: Belgian nursing minimum data set

BP: Blood pressure

BS: Base-stations

BUN: Blood urea nitrogen

CABG: Coronary artery bypass graft

CATS: Clinical activity tracking system

CDF: Cumulative distribution function

CDHB: Canterbury District Health Board

CI: Confidence interval

CPR: Cardiopulmonary resuscitation

CT: Computed tomography

C_{time}: CATS recorded activity time

CV: Computer vision

CVL: Central venous line

CVP: Central venous pressure

ESICM: European Society of Intensive Care Medicine

FiO_2: Fraction of inspired oxygen

GCS: Glasgow coma score

GICU: General ICU

GIRTI: Italian multicenter group of ICU research

GPS: Global positioning system

Hb: Hæmoglobin

HCO_3: Bicarbonate

Hct: Hematocrit

HDEC: Health and Disability Ethics Committees

ICP: Intracranial pressure

ICU: Intensive care unit

IF: Infrared

IQP: Inter-quartile range

IV: Intravenous

K: Potassium

LOC: Level of care

LOS: Length of stay

LPM: Local position measurement

MAP: Mean arterial pressure

MBP: Mean blood pressure

MICU: Medical ICU

mmHg: Millimetres of mercury

mmol/L: Millimole per litre

MT: Measurement Transponder

Na: Sodium

NAS: Nursing activity score

NEMS: Nine equivalents of nursing manpower

N/P: Nurse-to-patient

OpenNI: Open natural interaction

OPS: Oulu patient classification

PaO2: Arterial oxygen tension

pCO2: Partial pressure of carbon dioxide.

PDMS: Patient data management system

PEEP: Positive end-expiratory pressure

pH: Potential of hydrogen

PICC: Peripherally inserted central catheter

PRN: Project research of nursing

RASS: Richmond agitation-sedation scale

RF: Radio frequency

RFID: Radio frequency identification

RN: Registered nurse

RT: reference transponder

SAPS: Simplified acute physiology score

SDK: Software development kit

SOFA: Sequential organ failure assessment

TISS: Therapeutic intervention scoring system

TOSS: Time oriented score system

UHF: Ultra high frequency

μmol/L: Micromole per litre

UWB: Ultra-wide band

WBC: White blood count

Wh: Width of human head

WLAN: Wireless Local Area Network

Wp: Width of a pixel segment

σ : Standard deviation value

Chapter 1 Introduction

The roles of nurses in the Intensive Care Unit (ICU) are of the same importance as medical tasks, and complementary to them. The medical responsibilities of doctors and specialists mainly comprise the diagnosis and treatment decisions necessary to preserve life and treat the patient's condition. In contrast, nurses develop the plan of care, working collaboratively with physicians, therapists, the patient, the patient's family, and other team members. Their goals focus on the regular care and treatment of patient illness to improve quality of life [1]. Nurses coordinate patient care across an interdisciplinary health care team, providing both interdependent and independent care [1].

Patients in the ICU are critically ill and are thus under constant and continuous nursing observation. Figure 1.1 shows a typical ICU patient, and the range of therapies and sensors used treatment and for 24-hour observation. A monitor mounted on the wall shows a patient's vital signs, such as blood pressure and heart rate. A mechanical ventilator provides breathing support to patients with respiratory failure. Intravenous (IV) fluid and medicines are supplied through a central venous catheter or other IV lines. Urine output is collected in a drainage bag. Nasogastric and intubation tubes require regularly cleaning using suction. All of these aspects, and more, are monitored full time and required for monitoring and/or treating evolving patient condition.

In addition to the patient workload demand shown in Figure 1.1, a patient's neurological condition is checked every few hours, including eye, verbal and motor response. Patient blood gases are also collected in every few hours. Dialysis machine, X-ray computed tomography (CT) scans, and ultra sound scans are also employed frequently according to

patient condition. All these patient demands for nursing effort are considered as direct nursing activities that are a part of overall nursing workload.

Nurses also carryout activities indirectly related to patient care, such as administration, communication with doctors and physiologists, consultation with a patient's family, training, researching, and recording notes. These 'softer' activities comprise a significant proportion of time during a typical working day. Both direct and indirect nursing activities make up the entire nursing intervention time, where direct activities may vary with patient condition and its evolution [2].

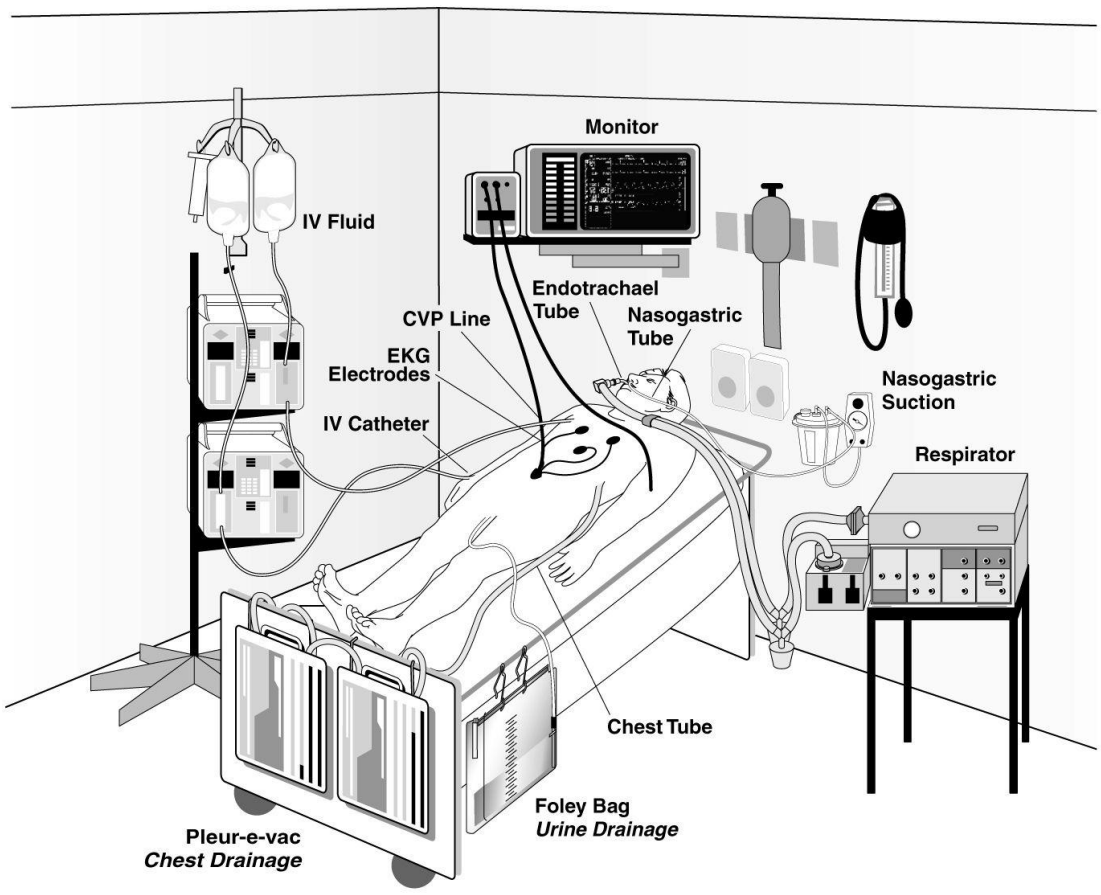


Figure 1.1: A typical intensive care unit patient. [3]

1.1 Nursing workload, ICU operating cost and patient outcome

Nursing is complex and involves a wide range of disciplines. It is also the main bridge between critically ill patients and their therapy. Thus, it is important to provide adequate nursing resources to satisfy patient demand. However, studies have shown that there is a mismatch between planned level of care (LOC) and practice, resulting in potentially huge losses of nursing resource, affecting patient outcome and the entire ICU [4-6]. Thus, it is important to optimally allocate nursing workload, as it should benefit nurses, patients and ICUs.

1. Benefit to nurses.

Nurses working in the ICU are exposed to considerable work related stress [7-9], and distress symptoms among staff have been described as being frequent [10, 11]. Studies have also identified high levels of burnout symptoms among ICU nurses [12-16]. In a study of nurses from 9 countries, Aiken et al. [17] reported that 33-60% of nurses reported high levels of burnout in 8 of the 9 counties. Many other counties have experienced similar burnout and job dissatisfaction issues [18-20].

It has been reported that 40% of hospital nurses have burnout levels exceeding the norms for health care workers. Job dissatisfaction among hospital nurses is four times greater than the average for all US workers [21]. The clinical impact of burnout may involve decreased well-being and increased sick leave among staff [22], which affects care. A high degree of emotional exhaustion among nurses has been shown to predict lower self-rated performances and higher intention to quit work [23, 24].

Burnout can be as result of too much work and/or too little time for recovery [25]. It has been shown that in hospitals with low nurse-to-patient ratio, nurses are more likely to experience burnout and job dissatisfaction [26]. High burnout scores are correlated with vulnerable personality, low job satisfaction, and high degree of job stress [27, 28]. Thus, allocating optimal nursing resources can avoid uneven workload, preventing nurse burnout and dissatisfaction.

2. Benefit to patients

Reduced nursing staffing in hospitals led to higher mortality rates after common surgeries [29, 30]. Research in Belgium found that the hospital mortality after cardiac surgery was significantly lower in hospitals with higher patient to nurse staffing ratios [31]. Likewise, data from a Swiss and North American studies suggested significant increased surgical mortality was associated with inadequate nursing staffing [32, 33]. In short, when patients receive adequate nursing care, there is less chance of developing infections and surgical complications, thus reducing LOS and mortality.

Research has also shown that adequate nursing care levels can improve ICU patient care. It was found that adding one patient per nurse was associated with a 7 % increase in the risk of death in the 30 days after admission, and a 7% increase in the risk of death by complications [34]. Increased staffing ratio was also associated with reduced deaths, LOS and surgical complications [35]. Some investigations have shown an inverse and statistically significant relationship between the percentage of nursing hours recorded and the development of pressure ulcers, urinary tract infection and postoperative infection [36], as well as between nursing hours recorded and medication errors, pressure ulcers, death and patient complaints, and LOS [37, 38]. Hence, more care can improve outcomes over today's baseline.

3. Benefit to the ICU.

The ICU represents the largest clinical cost centre in a hospital, with expenses estimated reach up to 20% of the hospital's budget [39-43]. For each patient in the ICU, their costs cover nursing, disposables, drugs, enteral nutrition, parenteral nutrition, beds hiring, haemofiltration, blood products, linen, physiotherapy, pathology and microbiology tests, and radiology investigations [44]. However, nursing staff represent the single largest fixed cost in the ICU (> 50%) [45]. Internationally, costs for personnel make up 30-69% of the total cost per patient [46-56]. Hence, getting staffing levels right is important clinically and economically, where today's demographic trends are increasing the tension between cost and quality of care.

The total cost per ICU patient also highly depends on the severity of illness and the length of ICU stay [57-60]. On study showed that a nurse staffing model with a higher number of registered nurses (RNs) led to an increase in the health personnel cost per patient day [61]. However, a greater number of RNs was also associated with improved patient safety and efficiency, thereby reducing patient length of stay and the costs of care in the long term [61].

Researchers have found that increasing the number of hours provided by RNs reduced mortality and yielded cost savings resulting from a reduced length of stay [62-64]. Therefore, inadequate nursing resources can lead to extended LOS, and increased infections, complications, need for mechanical ventilation, diagnostic procedures, invasive monitoring, and amount of drugs and blood products. These increases thus lead to an increase in daily cost per patient [65-69]. Additionally, considering fluctuations nursing workload over time, it is important to maintain the adequacy of nursing staff [70]. Inadequate numbers of nurses

could cause more harm to patient recovery and extend patient LOS, which would increase ICU cost. Hence, it may be more reasonable in the long run to be slightly over-staffed than to have inadequate numbers of nurses.

The basic observed relation between nursing workload, patient outcome, and ICU cost in these studies is shown in Figure 1.2, where nurse-to-patient ratio is the main parameter. An optimized nurse-to-patient ratio could reduce patient mortality, increase nurse job satisfaction, and reduce ICU cost, since ICU cost is significantly determined by patient LOS and the number of nurses. Nurses with higher job satisfaction are also less likely to make clinical errors [71], which could also further reduce patient mortality and LOS.

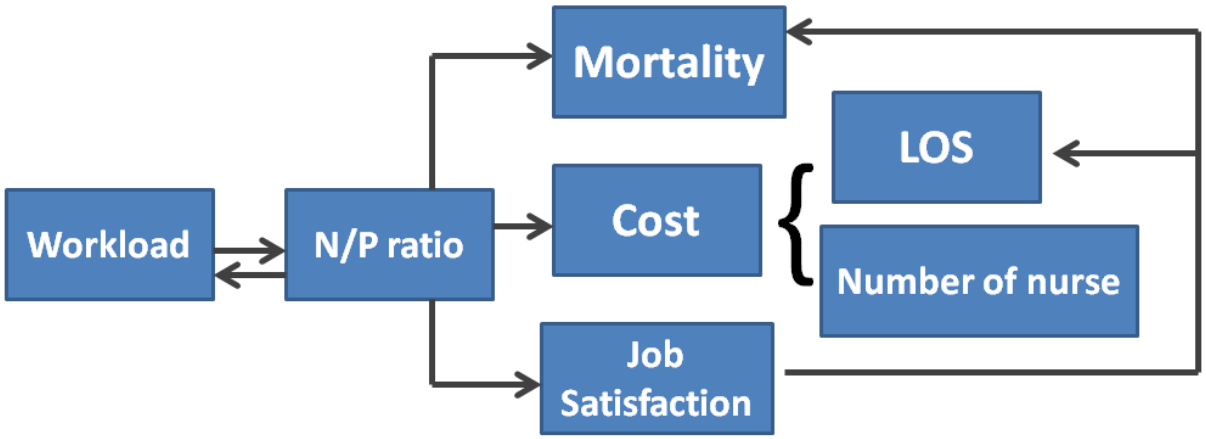


Figure 1.2: Correlation between nursing workload, patient mortality, nurse job satisfaction, ICU cost, and nurse-to-patient ratio.

1.2 Nurse workload is difficult to quantify.

Quantifying nursing workload could lead to generating an optimal nurse-to-patient ratio. It would thus be possible to allocate the right amount of nursing manpower to individual patients, benefiting patients, nurses, and the ICU. However, nurse workload is difficult to quantify [72].

1. Workload is difficult to conceptualized [73, 74].

Lysaght et al. [75] stated that workload can be defined as 'the relative capacity of respond'. Backs et al. [76] stated that workload is a construct used to describe the extent to which an operator has engaged the cognitive and physical resources required for a task performance. Weinger et al. [77] stated that workload is a multidimensional and complex construct, that is affected by external task demands, environmental, organizational and psychological factors, and perceptive and cognitive abilities. All three statements show that workload is a difficult concept to define. In addition, factors, such as environmental, organizational, and psychological factors also play a role in defining nursing workload.

2. Nursing is multi-task work.

Researchers have categorised nursing activities [2, 78-80]. In particular, most nursing activities can be divided as 'directly related to patient' and 'indirectly related to patient'. These 'directly related to patient activities', or direct interventions, refer to nursing work that can directly affect patient recovery and mortality. These activities are summarised and listed in Table 1.1 [2]. The 'indirectly related to patient activities', or indirect interventions, refer to nursing work that is not directly related to patient recovery, but supports nursing procedures and patient care. These indirect interventions are summarized in Table 1.2.

Nursing is clearly a multi-task form of work that requires the nurse to perform multiple activities simultaneously. For example, when a nurse checks body temperature, he/she may also be engaged with drug delivery. This complexity inherently makes quantifying nursing work a challenging task.

Table 1.1: Nursing work direct related to patient

1	Standard monitoring	Hourly vital signs; Electrocardiographic monitoring; Routine 24-hour fluid balanced and hourly neurologic checks.
2	Laboratory	Arterial blood gases and biochemistry studies.
3	Medication	Intravenous antibiotics; Parenteral chemotherapy; Intravenous medication; Potassium infusion; Acute digitalization; Anticoagulation; Vasoactive drugs.
4	Routine dressings	Dressing changes and extensive wound treatments.
5	Ventilation, supplementary ventilator care, and airway care	Controlled ventilation with or without positive end-expiratory pressure (PEEP); Supplemental oxygen; Spontaneous respiration via endotracheal tube; Care of artificial airways; Suctions.
6	Fluid replacement	Frequent infusions of blood; Replacement of excessive fluid loss.
7	Dialytic techniques	Check dialysis machine; Change dialysis machine parameter; Cleaning machine.
8	Single or multiple interventions in and out ICU	Pacemaker; Nasotracheal or orotracheal intubation; Emergency endoscopy or bronchoscopy; Cardioversion; Lavage of acute gastrointestinal bleeding.
9	Patient support	Helping the patient to understand and accept his/her clinical condition.
10	Patient communication	Communication with the patient; Informing, Observation and maintenance of the psychic condition; Taking measures to maintain or improve the capacity of communication.
11	Safety	Hourly vital signs; Electrocardiographic monitoring; Routine 24-hour fluid balanced and hourly neurologic checks.
12	Comfort	Arterial blood gases and biochemistry studies.
13	Lifting	Intravenous antibiotics; Parenteral chemotherapy; Intravenous medication; potassium infusion; Acute digitalization; Anticoagulation; Vasoactive drugs.
14	Assisting	Dressing changes and extensive wound treatments.

Table 1.2: Nursing work indirect related to patient

1	Family	Contact with, support, and consult patient family members.
2	Other disciplines	Contact with other disciplines, such as technical service, physiotherapy, laboratory, radiology, for the patient or equipment of one patient.
3	Coordinating tasks	Consultation with the team, reporting, work council, consultation with doctors.
4	Paperwork	Reporting, registration and administrative tasks.
5	Equipments	Taking care of equipment, such as maintenance, cleaning, gauging
6	Domestic activities	Cleaning waste according to instruction; supply maintenance; Refilling the supplies for a patient.
7	Activities not relating directly to a patient , ensuring everything fits together as it should	Meetings dealing with organizational issues; Making duty-rosters; General refilling of supplies for the whole team; Trainee supervision; Research activities; Following professional training in time of service; Contact with the general hospital services.
8	For nurses themselves	Taking a break; Going to the toilet; Waiting; Chatting.
9	Everything which does not fit any above mentioned categories	Patient observation only.

3. Many possible factors could affect nursing workload.

Nursing involves many aspects including interaction with patients, other disciplines, and equipment. In particular, indirect nursing work is similar from patient to patient, and consumes a smaller portion of all nursing care [2]. Thus, the purpose of this research is to find the correlation between nursing workload and patient oriented factors, generating a guideline to help allocate optimized nursing resources to specific patients.

1.3 Current workload assessment tools

Quantifying nursing workload and the optimal allocation of nursing resource in the ICU can benefit patients, benefit nurses, and benefit the ICU. Several studies were carried out and tools were developed in the last few decades to quantify nursing workload. Their goal was to better allocate nursing resources, and better understand what contribute to nursing workload.

The therapeutic intervention scoring system (TISS) was created in 1974 [81], and updated in 1983 [82]. It was designed to evaluate patient severity. The project research of nursing (PRN) score was elaborated during 1980-87, and was designed to assess nursing workload [83]. OMEGA [84] was developed in 1986, and describes 86 therapeutic interventions, grouped in 3 categories, measured at the end of ICU stay, thus representing a measure of global workload and use of resources.

The time oriented score system (TOSS) [79] was created in 1991 and represents a direct temporal evaluation of nursing workload. EURICU-1 [85] aims to categorize patient into 4 groups, and each patient category is assigned a correlated nurse-to-patient ratio. TISS-28 [2] represents a simplified TISS-76 score containing only 28 therapeutic interventions. It stated a

nurse can deliver work equal to 46 points per 8-hour shift, which transfers each TISS-28 point to 10.6 minutes of each 8-hour shift. Nine equivalents of nursing manpower (NEMS) [86] further simplified TISS-28 to 9 equivalent therapeutic interventions, where each nurse can deliver 45-50 points per day. Both TISS-28 and NEMS are patient oriented score systems, evaluating nursing workload based on patient potential demands and relative severity level. The nursing activity score (NAS) [78] is derived from TISS-28, and added 5 new items that are more nurse oriented, aiming to describe nursing activities not necessarily correlated to severity of illness. It captures 81% of nursing time, while TISS-28 only captures 46% of nursing time. However, these 5 new added items are not accessible from patient daily 24-hour charts, and requires subjective nurse survey feedback during each shift, which is subject to variability and thus not possible in real-time.

These current nursing workload assessment tools can gather information explaining the intensity of nursing work. However, they are subjective, requiring nurses or researchers to collect nursing information hourly or daily. Thus, there is a need to develop an automatic system that can objectively collect nursing work information.

1.4 The possibility of automatic system to quantify nursing workload

In a recent study, Adomat et at. [87] used a video camera to record nurse activity in ICU. They provide a novel method to classify patient-nurse interaction. However, this technique remains subjective, requires experienced nurses to classify the nursing activity and behaviour, and thus demands significant manual labour that is not available. In addition, it may involve ethical issues on patient and nurse privacy. Thus, there is clear need of an automated system that can measure activity non-invasively and preserving patient and nurse privacy to overcome these obstacles.

Thanks to the development of tracking technology and computer vision, continuously tracking is possible to be applied for observing nurse work in ICU. Global positioning system (GPS) and local position measurement (LPM) are two commonly known positioning systems being widely used in navigation and workload tracking [88, 89]. GPS and LPM use a tracking device to send signals of the current location of the device to a satellite or base station to point the current location [90]. LPM is more widely used in industrial tracking applications and indoor tracking usage [91]. In addition, the following technologies all have been used in tracking and positioning: 1) Radio frequency identification (RFID) [92]; 2) Cellular-Based, which is widely used for indoor mapping and localization applications [93]; 3) Ultra-wide band (UWB) technology [94]; 4) Wireless Local Area Network (WLAN) [95]; 5) Bluetooth, which can be applied for indoor positioning situations too [96]; 6) Ultra high frequency (UHF) technology [97, 98]; 7) Infrared (IF) detection [99]; and 8) Computer vision (CV) [100]. These systems have shown the basic potential to quantify nursing workload in an automated fashion.

1.5 Research objectives

In this research, the first part focuses on the development of a novel automatic system that can objectively quantify nursing workload. This new system offers the ability to continuously collect nursing workload in the ICU or any similar acute bed space. In particular, it includes system hardware and software developments, system simulation in an experimental environment, system set up in the clinical environment, and system validation in clinical trials.

The second part focuses on its clinical application. It generates a novel approach to analyze what specific clinical or patient factors could possibly impact the intensity of nursing work. In particular, it explains the procedure of patient data collection and current patient severity assessment tools. It then compares nursing workload with these patient clinical indicators, such as their illness acuity, age, gender, LOS, and diagnostic code.

1.6 Structure of thesis

This thesis is separated into two main parts. The first part, Chapters 2 to 6, discusses the development of this novel automatic system, the clinical activity tracking system (CATS). It also includes system laboratory simulation, installation in the ICU, and system validation in clinical trials. The second part includes Chapters 7 to 10, which discuss data from 10 months of clinical data collection using CATS and analysis in the Christchurch Hospital ICU. Correlation between nursing workload and patient clinical data are studied. The structure of thesis is presented as follows:

Chapter 1: Introduction. This chapter presents the background knowledge, research objectives and the structure of this thesis.

Chapter 2: Comparison of Different Tracking Systems to Apply in Intensive Care Unit. This chapter focuses on evaluating 4 possible methodologies to automate nursing workload quantification and selects the optimal methodology for further development.

Chapter 3: Design and Development of Clinical Activity Tracking System (CATS). This chapter further discusses the development of the clinical activity tracking system (CATS), explaining the details of developing system hardware, software, and the performance.

Chapter 4: CATS Performance in an Experimental Environment. This chapter presents the test of system reliability and consistency in a simulation environment. Specific tests were designed for the CATS system testing. Results showed that the CATS can be used in a clinical environment for nursing workload quantification.

Chapter 5: CATS Setup in Clinical Situation and Its Performance after Data Post-Processing. This chapter presents CATS setup for clinical application in the Christchurch Hospital. Different filtering algorithms were developed to reduce noise. It shows that the algorithms were able to reduce noise signals that are not relevant to nursing interventions.

Chapter 6: Validation and Preliminary Results. This chapter validates CATS ability to quantify bedside workload. The workload quantified by CATS is validated with manual clinical observation. A preliminary study for the first 30 days and 60 days of nursing intervention distribution is also presented.

Chapter 7: Comparison of different clinical scoring systems and relative results. This chapter presents the different patient severity assessment tools and nursing workload assessment tools, TISS-28, NEMS, APACHE-III, SAPS-II, APACHE-II, and SOFA. These scores were generated from patients included in the CATS study. Results showed that it is possible to use patient severity scores to predict nursing requirement and corresponding nurse-to-patient ratio.

Chapter 8: Correlation between CATS calculated nursing intervention and patient sedative conditions. This chapter analyses the performance of current sedative assessment tools,

indicating the different sedative level during daytime and night time. In addition, it compares nursing workload with different sedative scores and different sedative drugs, testing patient nursing demands based on sedative conditions.

Chapter 9: Correlation between CATS calculated nursing intervention and different patient clinical conditions. In this chapter, nursing workload is compared with different factors that could affect patient nursing demands, including time of a day, patient severity scores, TISS-28, NEMS, patient age, gender, type of admission, intubation condition, and FiO2 level.

Chapter 10: Patient specific study and recommended nurse-to-patient ratio. In this chapter, 6 patients are selected to analyse variation of nursing demand, and possible factors influencing patient nursing demands are tested. In addition, a recommendation is made for nurse-to-patient ratio based on different time of the day and different patient illness severity levels.

Chapter 11: Conclusions, limitations and Future work. This chapter summarizes all the conclusion of previous chapter, points the limitations of system application, and lists future works for this research.

Chapter 2 Comparison of Possible Tracking Systems to Apply in Intensive Care Unit

Quantify nursing interventions and workload near the patient bedside area in the Intensive Care Unit (ICU) is a very challenging task. Traditional scoring systems have been developed to assess nursing intensity, such as the therapeutic intervention score system-28 (TISS-28) [2, 81, 82, 101, 102] and nurse activities score (NAS) [70, 78, 80, 103, 104]. Each TISS-28 point is theoretically equivalent to 10.6 minutes of nursing work in an 8-hour shift, and each NAS point corresponds to 14.4 minutes nursing work in a 24-hour shift [102]. However, both scoring systems require experienced researchers or nurses to complete specific form every 24 hours to account for changing patient condition. They are thus subject to variability and may not be able to capture specific trends. Finally, they have not changed in many years, and thus may not be as relevant or calibrated to the modern ICU environment. In addition, their applicability across different clinical practice may also be questioned. Hence, an automatic system that can objectively quantify nursing activity or workload in site is required.

To develop an automatic nursing workload detection system at the patient bedside, there are a few important issues that need to be considered and addressed. For example, the system, while capable of calculating the nursing workload automatically, must also protect both patient and nurse privacy [105-109]. In addition, the system should be robust and relatively noise free, separating what could be true workload from other inputs or forms of noise. Another requirement is that the system should be minimally obstructive or invasive of current ICU bedside workload, which is already laborious and strenuous [83, 110, 111]. Hence, the

system must not only fulfil the ability to automate calculation of activity and workload, but also consider other factors revolving around the project.

In this chapter, several potential approaches to continuously track nurse movement are presented and compared. These proposed approaches are reviewed and ranked based on the overall requirements enunciated. The system that ranked highest in the specific-scoring is further investigated and developed into the clinical activity tracking system (CATS) that is used in this research.

2.1 Introduction

Currently, there is no standard, automated method to consistently quantify patient and bedside nurse interaction. Adomat et al. used a video camera to record ICU nursing activity [87] and concluded that existing nurse-to-patient ratio classification methods are inappropriate. This video recording method does provide a general outline to optimize nurse-to-patient ratio. However, it is laborious, and subject to variability as it required experienced nurses to classify the recorded nursing activity and behaviour manually. Thus, there is a need for a clinically feasible approach to automatically record nursing movement around the bedspace, to enable analysis of the correlation between nursing activity and patient outcome.

Object positioning and tracking have been widely used in other research fields, such as human ergonomics and workspace management related studies [112-114]. Global Positioning System (GPS) and Local Position Measurement (LPM) are the most commonly known positioning systems being widely used in navigation and tracking [115-119]. GPS uses a tracking device to send signals of the current location of the device to a satellite to pin point the current location [90]. LPM uses similar concept as GPS, but at a smaller scale. It is

widely used in industrial tracking applications and indoor tracking usage, which is often required to know the position of a target within a locally restricted area [120-125]. However, all these systems require the nurse or other users to wear a tracking device, which can be invasive of privacy outside the bedspace.

According to the technology being used, positioning and tracking systems include the following categories: 1) Radio frequency identification (RFID), for example, SpotON, LANDMARC and RADAR are well-designed indoor location sensing systems based on RF signal technology [126-130]; 2) Cellular-Based systems, which are widely used for indoor mapping and localization applications [93, 131]; 3) Ultra-wide band (UWB) technology, which is used for precision localization applications for tracking high valued asset in hospital and factories [132-134]; 4) Wireless Local Area Network (WLAN), which is utilized in location determination and estimation [135-140]; 5) Bluetooth applied for indoor positioning situations [141-144]; 6) Ultra high frequency (UHF) technology that is also used for finding indoor objects [145, 146]; 7) Infrared (IF) detection, which can be used for specific target detection and fire detection [99, 147-149]; and 8) Computer vision (CV), which is widely used in facial reorganization, traffic optimization, color filtering and skeleton detection along with a wide range of security applications [100, 150-154]. All these positioning and tracking technologies have their unique usage in all sorts of different situations. Several, but not all, require the end users (nurses) to wear a tracking sensor of some form.

2.2 Requirements for the tracking system

In this study, the detection area focuses on patient bedside and does not extend beyond that area. An example of the ICU patient bedside layout is shown in Figure 2.1. This area of interest, also known as the nursing area, is where most clinical or nursing activities take

place. Such clinical nursing activities include cleaning patient wounds, daily cleaning, administration of intra-venous drugs or fluids, managing mechanical ventilation, and observing and recording vital signs.

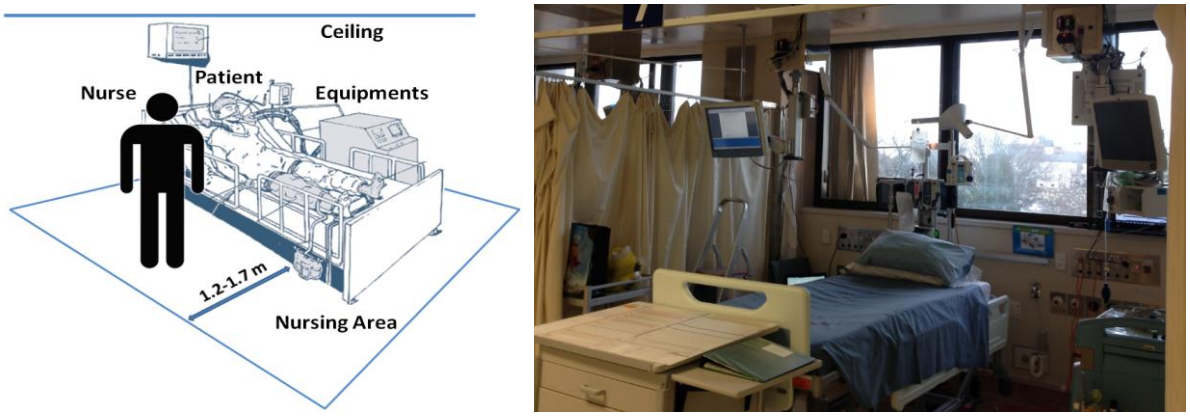


Figure 2.1: Left: Layout of one unit in ICU; Right: a typical Christchurch ICU unit.

Thus, potential or proposed automated activity monitoring systems are required to fulfil several criteria:

1) **Accuracy:** The ability to accurately detect clinical staff, especially when there is noise or other objects.
2) **Continuity:** The ability of the system to continuously track the candidates. This criterion is important, as clinical activities at the bedside are not necessarily routine and can be quite variable in activity and intensity depending on patient condition.
3) **Multiple tracking:** The ability to track multiple people or activities from two or more people in the area of interest. Clinical activities that are labor intense require more clinical staff.
4) **Covered area:** The amount of detection area the can be covered by the system. Larger areas with higher resolution are preferable, although still limited to the bedspace.

5) **Positioning:** Positioning is an important feature, where the location of each tracked activity may provide information of the detail clinical activity. Higher accuracy of position detection will be given a higher score, as it will allow greater precision in grading the clinical intensity of monitored activity.
6) **Privacy:** One important criterion to evaluate is whether the system needs to gather a nurse's personal information or position via a sensor on the nurse. A system that protects the nurses working environment privacy will thus have a higher score.
7) **Potential cost:** This criterion evaluated the cost involved based on the equipment required per bed and a lower cost will have a higher score.

The proposed systems are scored using a decision making based Weighting and Scoring Method [155].

2.3 Different tracking system designs

In this research, 4 detection methods were evaluated, of which 3 use a video recording and 1 requires the nurse to wear a signal transmitting device. The methods using any form of video camera are: 1) Facial detection; 2) Uniform/color detection; 3) A novel tracking system used Kinect. The method with signal transmitting device is 4) Local Position Measurement (LPM). The principle of each method is introduced and the advantages and disadvantages of each method are compared and checked against the requirements stated.

2.3.1 Facial detection

The application of facial detection and facial recognition is widely used for biometric identification, video conferencing, indexing of image and video databases, security systems, and intelligent human–computer interfaces [152, 156-159]. Various different detection

patterns have been developed to efficiently recognize, categorize, and track a human face [160-164]. Using a video camera and a detection algorithm, a human face can be recognized based on several features, such as eyes balls, skin color, and face shape. In this particular application, a facial detection method was implemented in C++, where the procedure is explained in detail in Appendix 2.1.

Facial recognition can accurately monitor nurses when they are in range of the monitoring and facing the camera. However, these methods require partial or full facial features for detection. In reality, facial features are not always present at the ICU bedside. For example, the nurses may be facing away from the camera while performing clinical activities. Thus, this method is significantly limited to the distinct facial features. It also poses privacy and compliance risks as specific nurses are identified.

2.3.2 Color detection

There are many applications using color detection techniques in computer vision, such as skin color detection, traffic light detection, and flame detection [165-169]. The combination of color detection and other algorithms is widely used in other applications, such as herbaceous crop detection, detecting groups of people, and human gesture detection [150, 154, 170-172]. In this application, nursing staff in ICU would have to wear distinct colored uniforms. Thus, color detection can be applied to track nursing activity without specific individual detection. In this application, the system implements 'OpenCV' [100, 173] and 'OpenCVBlobsLib' libraries [174] for image processing. System detected nurse uniform color (blue) can be highlighted in a 'Black&White' image to protect nurse privacy. Tracking this color cluster, as shown in Figure 2.2, enables tracking of nurse activity. This procedure is demonstrated in Appendix 2.2, and can be generalized to specific patterns or similar markers.

This method greatly reduces the need for specific individual feature detection. However, there are still disadvantages to this approach. First, color detection is exposed to significant non-clinical activity noise if an object or non-clinical person with similar color enters the detection area. Second, color detection or filtering is also limited in range. Thus, only nurses with a set color uniform can be detected. This color range can be extended to account for every possible combination. However, that approach would also increase the risk of erroneous detection. Third, it is difficult to track multiple nurses, especially if several nurses are overlapped in one frame. Fourth, environmental light can influence system robustness. For example, blue exposure has different color range under natural sunlight or LED lights. Last, the position of nurse is known in a 2-dimensional space that makes it more difficult to know their exact location in that space.

Figure 2.2: Uniform color detection.

2.3.3 Inferred detection

Infrared depth sensors are widely used in many applications. For example, spotted infrared target automatic detection and tracking, and satellite fire detection [99, 147]. Using this concept, a camera and infrared depth sensor can be fixed on the ceiling, facing downwards to

capture nurse location. In particular, the depth sensor allows objects/ personnel within a set height to be detected in the tracking area. Figure 2.3 shows a sample image captured by the camera and depth sensor, where three candidates were identified. The left image shows the depth image captured from depth sensor and the right image shows the color information from the camera. The advantage of this method is that it can easily pin point the floor location for each nursing or clinical activity. However, the major disadvantage is a limited tracking area dependent on the sensors field of view, which trades off with accuracy. In particular, the location of the infrared sensor is limited to ceiling height, which bounds the total area of infrared projection, and thus the total tracking area. More details of this approach are explained in Chapter 3.

Figure 2.3: The depth sensor captured image and the color image.

2.3.4 LPM

Unlike Global Positioning Systems (GPS), local position measurement (LPM) is a more precise approach to locally track targets in a limited space or area. It is widely used in many areas, such as tracking of a single sportsman or whole teams, tracking of autonomous vehicles in industrial warehouses, and positioning vehicles and carts in large airports [152]. Figure 2.4 shows the basic LPM concept [120]. LPM requires at least four base-stations (BS), and they must be arranged in exactly known positions around the field of interest. The target

is called the measurement transponder (MT). The unknown position is determined by means of time-of-flight measurements of electromagnetic waves travelling from the transponder to the BS. The synchronization problem is solved by applying an additional reference transponder (RT) at a well-known and fixed position. The advantage of using LPM is that the 3D position of the nurse can be accurately identified at all times without specific identification. Multiple tracking is also easy to achieve.

However, LPM typically contains some sensors for the target to carry, to provide position reference. The most common possible choices of wireless transmission media are radio frequency (RF), optical communication (laser) and infrared [128]. No matter which type of sensor, the nurse is required to wear a transmitter tag from which the base-station can receive a signal. For example, nurses would have to carry a RF ID bandage [126] during their shift. Their position can be accurately recorded all the time. However, this extra requirement affects work satisfaction and provides an entryway for more intrusive monitory. In addition, it requires more base stations and other equipment around bedspace.

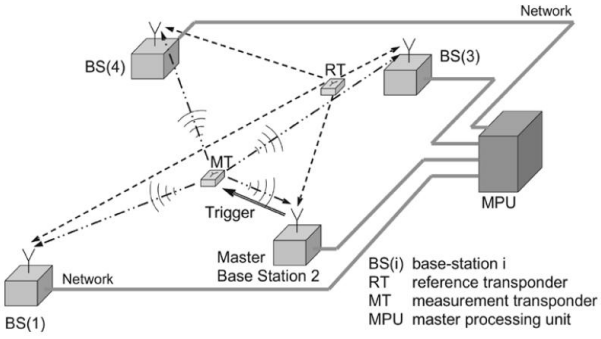


Figure 2.4: Basic arrangement of transponders, BSs, and MPU, and the signal flow within the LPM system.

2.4 Comparison of different systems

For these 4 different methods, there are 7 attributes considered in Table 2.1: Accuracy, Continuity Detection, Multiple Tracking, Covered Area, Positioning, Privacy and Potential Cost. Their weights are given according to importance in successfully tracking a nursing activity trajectory at the bedside relative to devices and areas of interest. Each attribute is scored from 0-5, where '5' signifies the criteria are met extremely well, and '0' signifies a solution dose not meet the criteria at all. The total scores are summed across the attributes, and the best solution selected.

Table 2.1: Comparison between different recognition and tracking approaches

		Requirement Score (0~5)			
	Weight	**Facial Detection**	**Uniform Detection**	**Infrared Depth Sensor**	**LPM**
Accuracy	10%	5	4	4	5
Continuity Detection	10%	3	5	4	5
Multiple tracking	10%	4	4	5	5
Covered area	10%	4	4	3	5
Positioning	20%	2	2	5	5
Privacy	20%	2	4	5	3
Potential Cost	20%	5	5	5	3
Total Score	100%	2.4	2.9	4.6	4.2

'Accuracy' evaluates when the system detects the object, whether the object is actually a nurse, especially when patient relatives or human size or height objects appear. Thus, for facial detection, it is required to recognize facial feature of the nurse and thus obtains the

highest score. LPM can continuously track specific nurse position, and thus also receives a 5. Uniform detection cannot ensure detected objects are a nurse, because family visitors or others may dress in similar colors as the nurse. Infrared cannot separate nursing intrusion from other objects either.

‘Continuity’ evaluates when nurses do appear in the detection area, whether the system can continuously record them, especially when they are not facing the sensor or are bent over the bed. LPM has the highest score as it can continuously record objects. Uniform detection could reliably track nurse motion when they are in the detection area. Infrared detection may lose the target if the nurse bends over beyond its detection range. Facial detection has the lowest score, as the nurse may not always face towards a fixed direction and sensor in many cases.

‘Multiple Tracking’ evaluates whether the system can record all nurses when these are multiple in the workspace, what the maximum number of people the system can record, and whether the system still works when the image is overlapped. LPM can always track multiple tagged targets, and receives the thus highest score. Infrared detection can also separate targets easily, as the sensor is placed on the ceiling. Uniform detection or facial detection may lose multiple targets when one nurse blocks another, and thus both receive lower scores.

‘Covered Area’ evaluates the size of the area and whether the system can cover the nursing area. LPM can cover the entire ICU and thus receives the highest score. Facial detection and uniform detection need to place the camera in front of the patient bed, and thus cover a larger area than the infrared detection. Thus these 2 methods get higher scores than infrared, but lower than LPM.

‘Positioning’ evaluates the ability to correctly record the position of the nurse at all time, especially the position where they carry out specific tasks or work. This location could be a 3-D location inside the ICU or a 2-D location around the bedspace to indicate where the nurse is located. LPM can generate very precise locations for tracked targets at all times, and thus given the highest score. Infrared detection can record a target’s 2-D location easily, as the sensor is placed on the ceiling. Uniform detection and facial detection cannot generate precise 3-D locations by one camera, and are difficult for 2-D location, and thus receive the lowest score.

‘Privacy’ evaluates whether the tracking system records nurse personal information, such as their facial features, or could do so, and also whether the system can stop recording them while engaged in private activities or away from the bedspace. Uniform detection and infrared detection do not require any personal information, and thus receive the highest scores. Facial detection needs to detect facial features, and thus gets the lowest score. LPM requires the nurse’s cooperation to wear a tracking tag, which would become an intrusive system, and thus gets a lower score.

‘Potential Cost’ evaluates the cost of equipment and the potential cost of installing and maintaining the system. Facial detection, uniform detection and infrared detection only require a single camera, infrared sensors and laptops. LPM costs much higher than the other 3 methods, and thus receives the lowest score.

Among these 4 methods, LPM and the Infrared Depth Sensor have shown the highest scores in accuracy as well as positioning, and in total in Table 2.1. Potential methods are thus

narrowed down between these 2. The Infrared Depth Sensor can much better protect nurse privacy than the LPM, as there is no need for nurses to wear transmitter tags. Considering that the Christchurch ICU has more than 100 nurses over all shifts for up to 20 beds, and many on-call nurses, asking permission of each of them is very challenging and likely to fail. In addition, infrared can record more information than the LPM. For example, the exact nursing activity can be recorded with a filtered camera, while LPM can only record time and position. This capability provides a better platform for the system for further expansion. Thus, the infrared depth sensing method is selected and further developed to for the application to automatically detect nursing activity at the patient's bedside.

2.5 Summary

After evaluating all methods, it was found that the infrared depth sensor detection method is best suited for the application in monitoring nursing activity and workload around an ICU bedspace. Thus, efforts are made to develop this method further and implement it in the ICU environment. In the next chapter, the development of this clinical activity tracking system is presented. The details of the hardware, as well as software coding used in the system, are described in detail in this Chapter.

Chapter 3 Design and Development of Clinical Activity Tracking System (CATS)

In the previous chapter, it was found that the highest scoring sensor choice for motion and nursing workload tracking, based on the evaluation metric used, is the infrared depth sensor. This method is further investigated and developed for this research application. The motion tracking system used for nursing workload detection is called the clinical activity tracking system (CATS). This chapter presents the development of the hardware and software components of CATS, and how it is set up in a simulated test and development environment.

3.1 CATS hardware component: Microsoft Kinect

CATS development is based around the Microsoft Kinect System. Kinect is a motion sensing input device developed and commercialized by Microsoft for the Xbox 360 video game console and Windows PCs [175, 176]. Based around a webcam-style add-on device for the Xbox 360 console, it allows users to control and interact with the console using simple gestures and spoken commands. This CATS system will use the motion sensor functions of this interface. A version for Windows was released on February 1, 2012 with a Kinect software development kit (SDK) for Windows 7 released on June 16, 2011 [177]. This SDK allows .NET developers to write Kinect apps in C++/CLI, C#, or Visual Basic .NET.

Kinect builds on software technology developed by a subsidiary of Microsoft Game Studios [178, 179]. The range camera technology was developed by PrimeSense (bought by Apple Inc. in 2013) [180, 181]. The device features a RGB camera, depth sensor and multi-array microphone running proprietary software, which provides full-body 3D motion capture, facial

recognition and voice recognition capabilities. The depth sensor, which is the particular sensor used here, is composed of an infrared laser projector combined and a monochrome CMOS sensor. It captures video data in 3D under any ambient light conditions [182]. The Kinect software is capable of automatically calibrating the sensor based on game play and the player's physical environment, accommodating for the presence of furniture or other obstacles.

Kinect is also capable of simultaneously tracking up to six people, including two active players for motion analysis with a feature extraction of up to 20 joints per player if viewing them head on. Thus, there is the capability to detect multiple individuals, and, via their actions, one can determine their purpose in the setting. Equally, the wearing of markers to enable identification of role (doctor, registrar, nurse, specialist, and family visitor) would enable ready identification of roles for this research, if this level of segregation was required.

Reverse engineering shows the Kinect sensor outputs video at a frame rate of 30 Hz. The RGB video stream uses 8-bit VGA resolution (640 × 480 pixels) with a Bayer color filter. The monochrome depth sensing video stream is in VGA resolution (640 × 480 pixels) with 11-bit depth, which provides 2,048 levels of sensitivity. The area required to play using Kinect is roughly 6 m^2, although the sensor can maintain tracking through an extended range of approximately 0.7 - 6 m. The sensor has an angular field of view of 57° horizontally and 43° vertically, while the motorized pivot is capable of tilting the sensor up to 27° either up or down. The horizontal field of the Kinect sensor at the minimum viewing distance of 87 cm, and the vertical field is 63 cm, resulting in a resolution of just over 1.3 mm per pixel. The microphone array features four microphone capsules and operates with each channel processing 16-bit audio at a sampling rate of 16 kHz.

Figure 3.1 shows the overall, relatively small sensor package within the Kinect. There are many applications established based on Kinect technology, such as limb detection, joint recognition, Kinect display games, hand gesture recognition, fall detection, and indoor mapping [153, 183-187]. With this capability, Kinect is suitable for this proof of concept research. Multiple Kinect units can be used to cover the working area of an ICU patient bedspace.

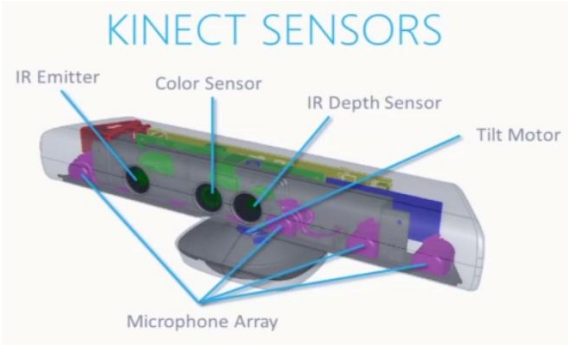


Figure 3.1: Kinect system image showing the overall sensor package. [188]

In this research, the Kinect is used as the main sensor unit and is mechanically mounted on the ceiling, facing downwards, to detect motion from above. Figure 3.2 shows the installation details of Kinect onto ceiling. Specifically, 8 neodymium magnets sit inside an acrylic glass board, which has been attached mechanically onto the ceiling. A stainless steel bracket is attached onto glass board and taped with Kinect base. The design of the bracket is included in Appendix 3.1.

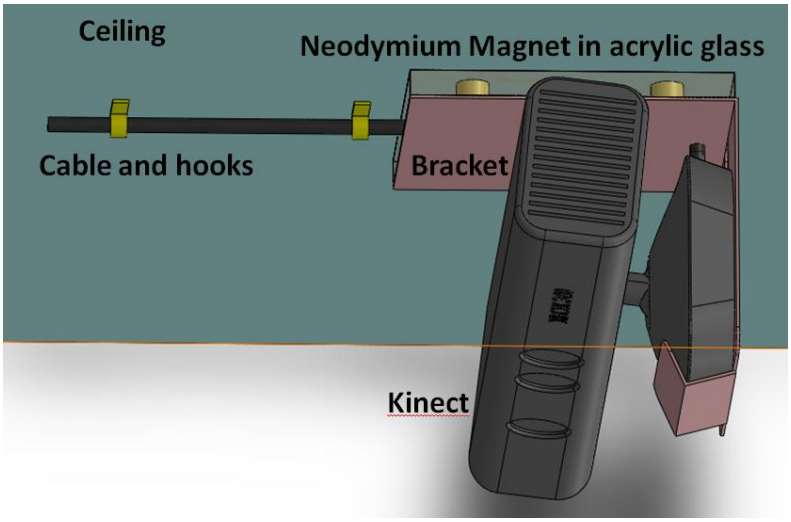


Figure 3.2: Mechanical installation of Kinect onto ceiling.

3.2 Kinect range of detection

In the Christchurch hospital ICU, the distance between the ceiling and the floor is 2.7 m. The CATS test system is first set up in a laboratory environment with similar 2.7 m height to simulate a part of the patient bedside area in the ICU. A schematic drawing of the experimental CATS set up and corresponding system variables is shown in Figures 3.3 and 3.4. When the system is set up in this configuration, the Kinect horizontal axis is the X-axis and vertical axis is the Y-axis.

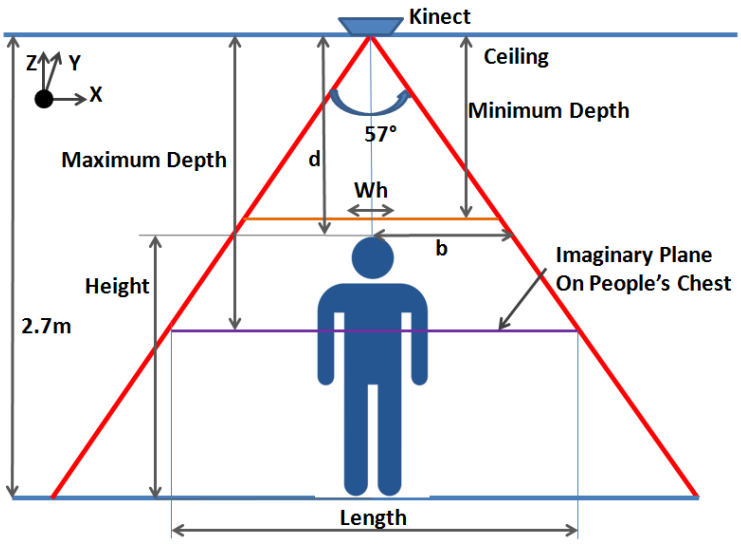


Figure 3.3: Front view of system configuration.

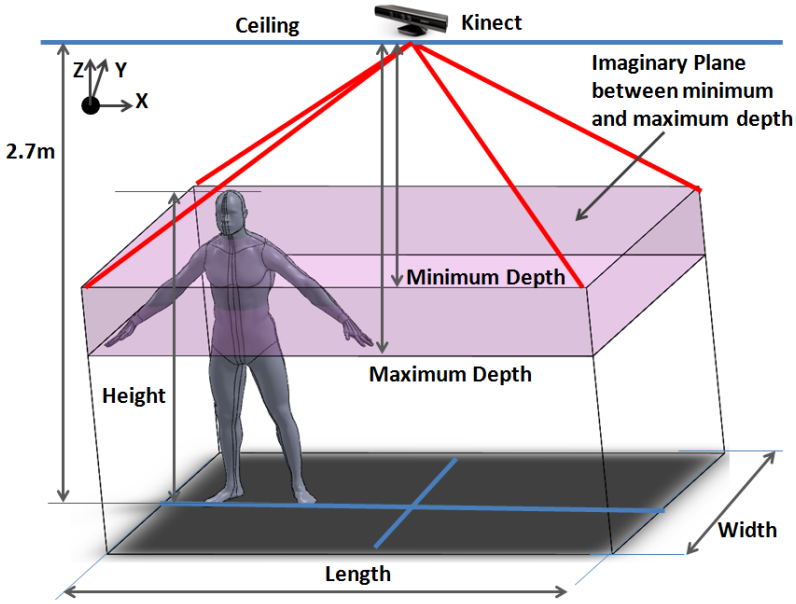


Figure 3.4: CATS configuration and geometry.

When detecting objects with the Kinect, the objects (humans) are imaged as blobs of pixels at a given depth and can be computed to estimate the actual size of the object. Figure 3.3 shows the computation of an object surface, in this case, the human head, width (*Wh*) corresponding to a pixel segment (*Wp*) detected in the Kinect in the X-axis. The distance between the human head and detection edge is defined as *b*. The distance from the ceiling to head is defined as *d*. The *Wh* variable is obtained by a proportion based on the total number of frame pixels along the X-axis (640 pixels), as shown in Equation 3.1:

$$b = d \cdot \tan\left(\frac{57°}{2}\right), \frac{Wp_{X-axis}}{640} = \frac{Wh_{X-axis}}{2 \cdot b} \Longrightarrow Wh_{X-axis} = \frac{2 \cdot b \cdot Wp_{X-axis}}{640} \qquad (3.1)$$

From this relation between *Wh* and *Wp*, the true length of the object detected within the sensing area can be estimated. Equally, if the segment belongs to the Y-axis, it is necessary to rotate the axis and replace 640 pixels with the 480 pixels sensor size along this axis, and 57°/2 with 43°/2, as shown in Equation 3.2.

$$b = d \cdot \tan\left(\frac{43^\circ}{2}\right), \frac{Wp_{Y-axis}}{480} = \frac{Wh_{Y-axis}}{2 \cdot b} \implies Wh_{Y-axis} = \frac{2 \cdot b \cdot Wp_{Y-axis}}{480} \quad (3.2)$$

Finally, if a segment is not parallel to either the X-axis or Y-axis, it is necessary to combine the orthogonal components during computation, as shown in Equation 3.3:

$$Wh = \sqrt{\left(\frac{2 \cdot d \cdot \tan(57^\circ/2) \cdot Wp_{X-axis}}{640}\right)^2 + \left(\frac{2 \cdot d \cdot \tan(43^\circ/2) \cdot Wp_{Y-axis}}{480}\right)^2} \quad (3.3)$$

Aside from *Wh* estimation based on the distance between *b* and *d*, there are also several important system variables that will affect the total tracking area, as shown in Figure 3.4. The variables are:

1. Height: Refers to the test candidate height (from the floor), which realistically varies from 1.52 to 1.90 m [189].
2. Depth: Refers to the depth from the ceiling to the floor. To capture test candidates, the Maximum Depth was set to the height of a shorter person's chest, 1.04 m from the ground, and the Minimum Depth was set above a taller test candidate's chest, 1.74 m from the ground.
3. Blob and Blob size: Every object that enters into the tracking area is known as a 'blob'. Every blob is identified by enclosing its contour with a rectangle, as well as a centre point.

The contiguous objects of interest in the covered zone are filtered using several empirically determined values. The system removes any blob size $Wh > 35000$ pixels (0.5 m × 0.5 m, e.g. patient bed) or $Wh < 5500$ pixels (0.2 m × 0.2 m, e.g. noise) being removed, according to

Equation 3.3. This filtering thus only captures blobs similar to human size, and ignores any others that are too large or too small.

Each detected object of interest (blob) is measured using pixel counters to detect its width and length. If the detected blob size is within the empirically set thresholds, the centre point's location of the blob in the area of interest is recorded. Up to 4 blobs can be detected and tracked simultaneously, which is a realistic maximum number of clinical staff for the section of bedside area and intended scenario.

3.3 CATS software component

To set up CATS and achieve the desired image processing, the CATS software was developed using the Microsoft Visual Studio 2010 Express [190] environment that includes the 'Kinect for Windows SKD' [191], 'OpenCV2.3.1' [100, 192-194] library, 'OpenNI' [195, 196] library, and the 'Kinect-OpenNI-Bridge' [197] driver. For this application, the CATS image processing component is implemented in a HP Probook 6550B laptop with 32-bit Windows 7 operating system.

3.3.1 OpenNI

OpenNI (Open Natural Interaction) is a multi-language, cross-platform framework that defines APIs (Application Programming Interface) for writing applications utilizing Natural Interaction [198]. OpenNI APIs are composed of a set of interfaces for writing NI applications. The main purpose of OpenNI is to form a standard API that enables communication with:

- Vision and audio sensors (the devices that 'see' and 'hear' the figures and their surroundings.)

- Vision and audio perception middleware (the software components that analyse the audio and visual data that is recorded from the scene, and comprehend it). For example, software that receives visual data, such as an image, returns the location of the palm of a hand detected within the image.

OpenNI supplies a set of APIs to be implemented by the sensor devices, and a set of APIs to be implemented by the middleware components. By breaking the dependency between the sensor and the middleware, OpenNI's API enables applications to be written and ported with no additional effort to operate on top of different middleware modules, creating a "write once, deploy everywhere" approach. OpenNI's API also enables middleware developers to write algorithms on top of raw data formats, regardless of which sensor device has produced them, and offers sensor manufacturers the capability to build sensors that power any OpenNI compliant application [199].

The OpenNI standard API enables natural-interaction application developers to track real-life (3D) scenes by utilizing data types that are calculated from the input of a sensor, for example, representation of a full body, a hand location, an array of the pixels in a depth map and so on. Applications can thus be written regardless of the sensor or middleware providers.

Figure 3.5 displays a three-layered view of the OpenNI concept with each layer representing an integral element:

- Top: Represents the software that implements natural interaction applications on top of OpenNI.

- Middle: Represents OpenNI, providing communication interfaces that interact with both the sensors and the middleware components that analyse the data from the sensor.
- Bottom: Shows the hardware devices that capture the visual and audio elements of the scene.

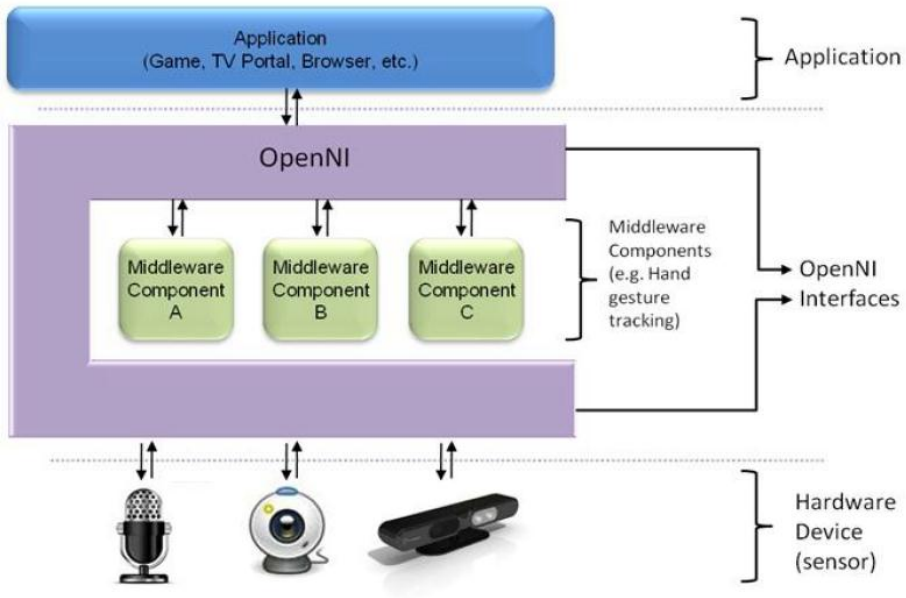


Figure 3.5: Three-layered view of the OpenNI Concept with each layer representing an integral element. [199]

To use OpenNI under a C++ 2010 platform, it is also necessary to install the 'Kinect-OpenNI-Bridge' [197]. This 'Kinect-OpenNI-Bridge' is an experimental module that connects the Kinect SDK to OpenNI and allows the applications to use Kinect for Windows over OpenNI. It is thus an enabling software module.

3.3.2 OpenCV

OpenCV is an open-source BSD-licensed library that includes several hundred computer vision algorithms, mainly aimed at real-time computer vision [200]. It has C++, C, Python

and Java interfaces, and supports the Windows, Linux, Mac OS, IOS and Android operating systems. The OpenCV environmental setup is explained in detail in Appendix 3.2. The OpenNI environmental setup is similar to OpenCV.

3.3.3 Kinect for Windows software development kit (SDK)

The Kinect for Windows software development kit (SDK) enables users to create commercial or Windows store apps and experiences that support gesture and voice recognition. It uses C++, C#, Visual Basic, or any other .NET language or Windows Store projection. The integrated developer toolkit includes sample applications with access to full source code, Kinect Studio, and resources to simplify and speed up application development [201].

3.4 Imaging processing procedures and storage

3.4.1 CATS software system initialization

The CATS system consists of two image algorithms: depth image and color image. The system imports the 'OpenCV' library [173] and 'OpenNI' library [202] to process image information gathered by the Kinect sensor. It is necessary to use a color image system, as system validation requires the captured depth image to be compared with color image. System initialization includes: 1) Depth and color variable assignments; 2) Initializing the Kinect device; 3) Extracting the depth image and color image, and writing them into the variables established in Step 1; and 4) Aligning the depth image and color image. In particular, each time the Kinect starts, the color and depth images are not overlapped well. Thus, it is important to align infrared image to correspond to the color image, so that these two images are overlapped, capturing same objects. Coding details are presented in Appendix 3.3.

3.4.2 Image filtering based on the range of minimum and maximum depth

The Kinect for Windows software development kit (SDK) [191] provides its own class for keeping captured images. It holds ‘Width’, ‘Height’, ‘Bytes per Pixel’, and raw data in bytes. For RGB video frames, each pixel holds 4 channels information in 32-bit XRGB format. Each channel has an 8-bit storage space, which can store values ranging from 0~255. For the depth image frame, each pixel holds a 12-bit depth of data in one channel, stored in two bytes with the upper 4 bits unused. Each pixel (each channel) can store values from 0~255. Depth data of value 0 means that objects at this position are out of detection range, either too close or too far, using pure black to represent value 0. In addition, a value 255 means that object at this position has reached the depth sensor minimum setting and become the brightest color, using a value of 255 to represent pure white.

When an object approaches from long distance to less than 0.6 m to the camera sensor, the pixel value changes from 0 to 255 and suddenly back to 0, and the image frames change from black to grey to pure white and then suddenly to black. The change is demonstrated in Figure 3.6.

The maximum and minimum detection range is set according to a predetermined population range. The maximum depth is slightly below human chest area or approximately 1.1 meters from the floor, and the minimum depth setting is around the human head area or approximately 1.8 meters from the floor. Figure 3.7 shows an example when people in the circle squat down in the CATS detection area, it causes them to disappear from the depth image. In addition, fixed objects, such as the table and chair, can be filtered, as they are above the maximum depth setting.

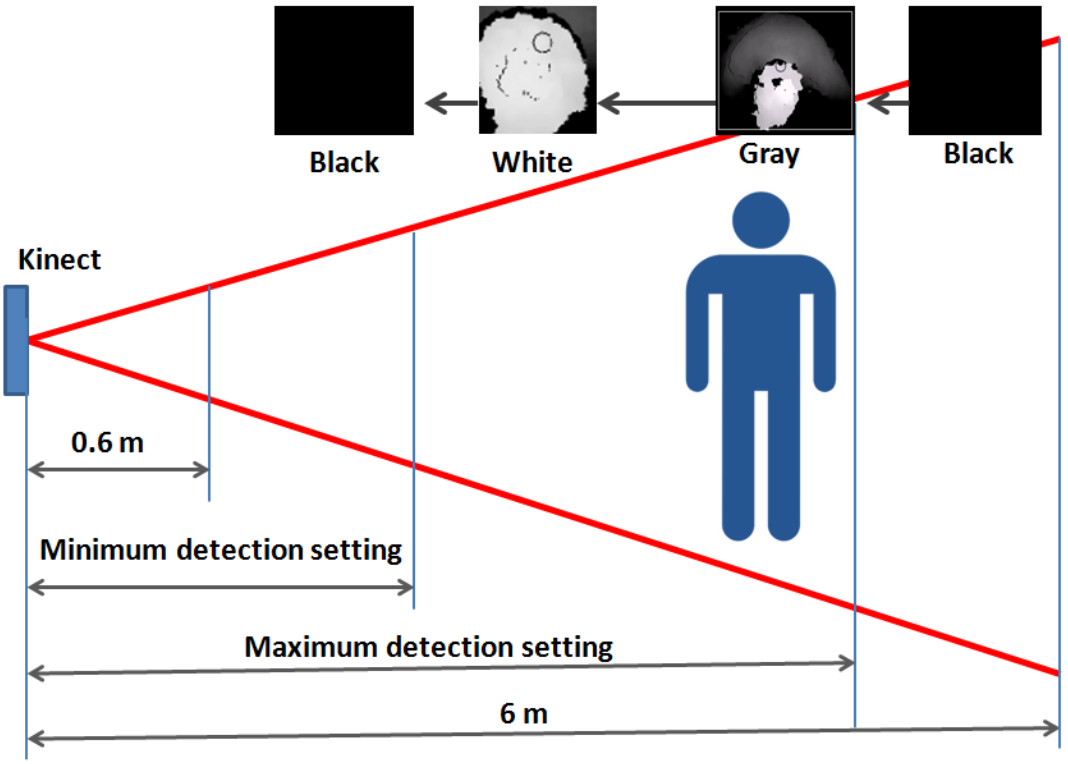


Figure 3.6: Detected object changes from black (out of detection area or above maximum detection setting) to gray (just entering maximum detection setting) to white (close to minimum detection setting), and then suddenly black (less than minimum detection setting).

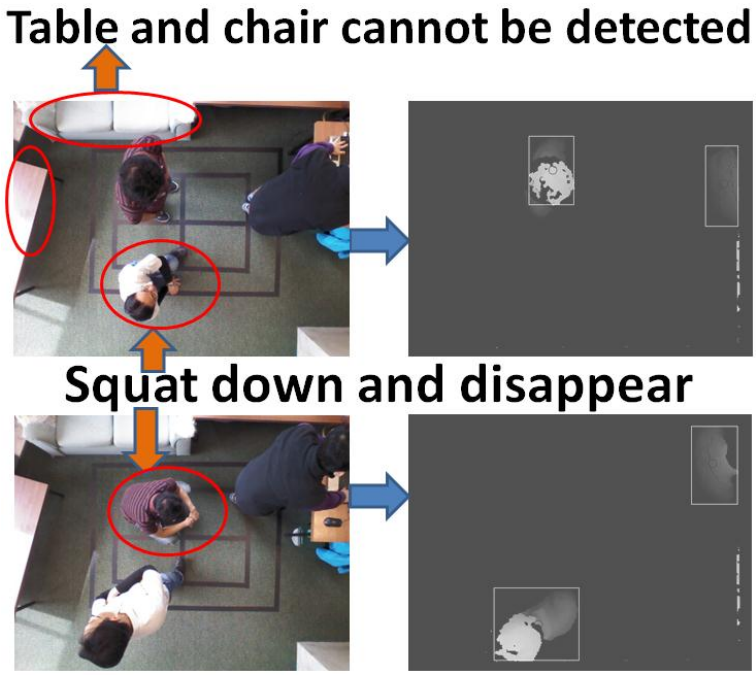


Figure 3.7: Object disappears when they are out of the Maximum and Minimum Depth range, thus eliminate the influence of table and desk, especially in ICU case, the influence from patient bed and curtain. In the top frames, the top left person stands and lower left squats. In the bottom frames, the roles are reversed. The third person, on the right, remains fixed partly squatting.

To filter objects or blobs in a specific depth range, the CATS system first extracts a depth image and writes it into an array (Figure 3.8 left image). Then, the system generates a depth image mask using the function 'createDepthMask' (in detail in Appendix 3.3). Any objects between the minimum and maximum depth are set as 0 and the rest are set as 255 (Figure 3.8 middle). Next, the combination of original depth image and generated mask is created, and the result is named as the 'Depth Image Visible' (Figure 3.8 right). In the Depth Image Visible, any pixel with value 0 in the mask maintains value 0 (black), while those pixels with values of 255 in the mask image are scaled from 0~255 (grey scale). This procedure discussed above is provided in detail in Appendix 3.3.

Figure 3.8: Depth image captured from Kinect is combined with generated mask to create ready for used depth image. Generated Mask can filter objects out of detection range, only keeping those between maximum depth and minimum depth.

3.4.3 Identification of human size blobs: filtering large and small blobs

The concept of a blob is defined as a cluster of pixels with values more than 0 and connected to each other in either rows or columns, as shown in Figure 3.9. Like the OpenCV and 'OpenNI' library, 'OpenCV' developed a publically accessible 'OpenCVBlobsLib' library [174]. It contains functions, such as blob extraction, blob filtering, and blob computation. The CATS software system implements 'OpenCVBlobsLib' to detect blobs and filter human size blobs. First, the system creates a variable defined as 'blobs' and extracts the blobs from the Depth Image Visible created in the last step. The system then filters blobs larger than the

upper limit and smaller than the lower limit, and prepares for further processing (Appendix 3.3).

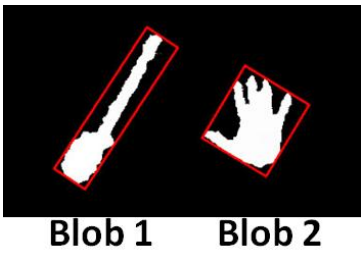


Figure 3.9: Connected arrays of pixels defined as blobs.

Based on the estimation from Equation 3.3, any blobs bigger than 35000 pixels and any blobs smaller than 5500 pixels are ignored, as shown in Figure 3.10. Figure 3.10(a) shows that the object/person is not recorded in the depth image if it exceeds 35000 pixels. Only blobs with a white rectangular box are recorded. The red circled blob exceeds 35000 pixels upper limit, and thus system does not record its position. This filtering thus ignores large objects, such as medical trolleys, X-ray machines, and other equipment. Figure 3.10(b) shows that when an object with less than 5500 pixels enters the detection area, for example, a hand, it is not recorded, as well. This filtering also acts as system noise filtering.

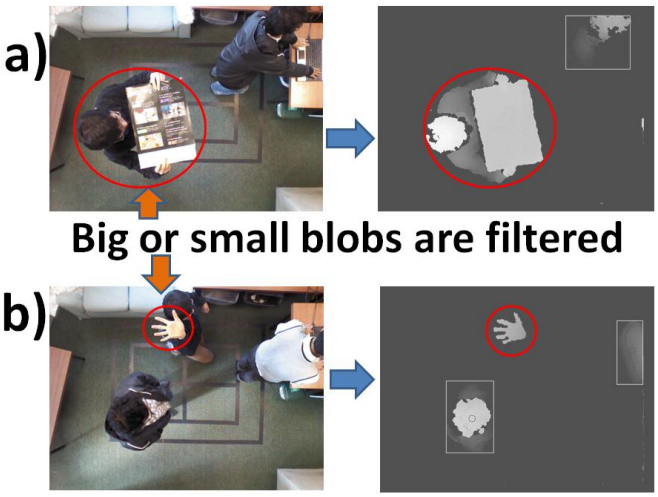


Figure 3.10: Objects bigger or smaller than human size are not recorded. (a): The large blob created by having a subject carrying a large tray close to their body is filtered. Position of person at the right top corner is recorded, as shown with a white rectangular box. (b): The small blob created by raising a person's hand is filtered, and the tracked blobs are distinguished by a box.

3.4.4 Identifying head-shoulder distance and blob grouping

For objects detected in Depth Image Visible, the corresponding central point is calculated, by averaging row and column indexes. A rectangular box is drawn to show the boundary of each blob. The average value of all pixels in each blob is also calculated, and this value is used to estimate the distance between objects and camera.

When all the blobs are detected, CATS software system allocates each blob an index number. The first blob is assigned as the brightest blob in group one. The system then calculates the distance between the first blob and the second blob by function 'getBlobDistance'. This function uses the central point of each blob to calculate the distance in terms of pixel, as shown in Equation 3.4:

$$\text{Blob Distance} = \sqrt{(x2 - x1)^2 + (y2 - y1)^2} \quad (3.4)$$

The first blob centre is (*x1*, *y1*) and the second blob centre is (*x2*, *y2*). If the distance is larger than 150 pixels (approximately 0.15 m), the second blob is assigned to a second blob group. If the distance is less than 150 pixels, it will allocate the second blob into the same blob group as the first blob. In each blob group, the CATS software system compares the average value of each blob and keeps the 'brightest' blob, and uses it to represent the blob group. An example of this image filtering is shown in Figure 3.11.

The reason for the implementation of this filtering algorithm is that when any person bends over, the body and head may be detected as two separate blobs in the depth image when it should be one. This algorithm has a limitation if there are two or multiple objects/ people that are too close (less than 150 pixels), and the blobs would merge into one. However, in reality,

this situation is unlikely to happen in a clinical bedspace, and if it does, it only lasts for few seconds. This filtering algorithm can also be found in Appendix 3.3.

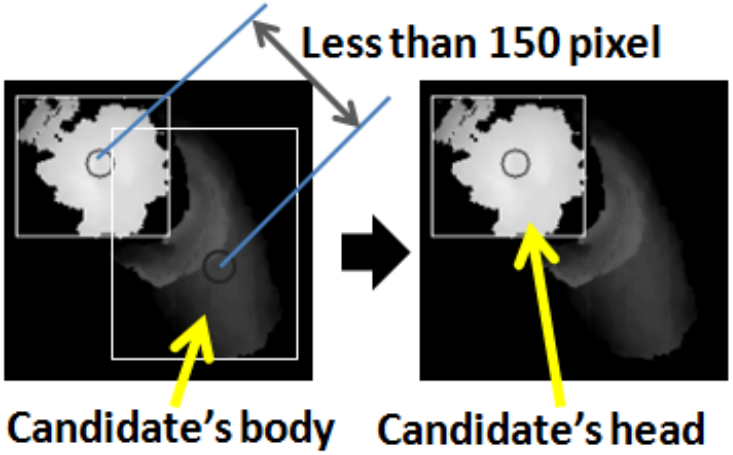


Figure 3.11: Example of multiple blobs within 150 pixels distance combining into one.

3.4.5 CATS data recording

CATS records the location of the blobs at 30 frames per second (fps). In every 1 second, the centre of each test candidate is written into a database. The process procedure for identifying the centre position of every candidate blob is as follows:

1) Blobs with different size and depth value are detected;

2) Blobs that are too small or too big are eliminated, leaving only 'human size' blobs;

3) If multiple blobs were detected, the distance between blobs is calculated;

4) If the distance between blobs is small, the multiple blobs near to each other are combined into one. Otherwise, they remain as multiple blobs;

5) The centre of all the blobs are recorded and stored in the CATS database.

One of the system requirements is that the system needs to track multiple people. Thus, it is essential for the system to separate and identify each person. After getting each blob's

position, they are compared with blobs in previous frames. Blobs with the minimum distance across consecutive frames are treated as the same person, as it is impossible that two people would swap positions in a single frame given the distances and scenarios involved, with the frame rate of 0.033 seconds.

For CATS, all object positions and corresponding times are stored in a plain text file. The depth and color image (video) with time were also recorded for comparison and validation. A sample of data recorded during a simulation is shown in Table 3.1. The corresponding depth and color image frames in Table 3.1 are also shown in Figure 3.12. The procedure can also be found in Appendix 3.3.

Table 3.1: One example of recorded blobs and related time

Year	Time	X of Blob 1	Y of blob 1	X of blob 2	Y of blob 2
20140821	103817	x0=563	y0=135		
20140821	103818	x0=548	y0=095		
20140821	103819	x0=298	y0=043	x1=547	y1=082
20140821	103820	x0=292	y0=042	x1=541	y1=076
20140821	103821	x0=295	y0=034	x1=547	y1=072
20140821	103822	x0=317	y0=057	x1=543	y1=075

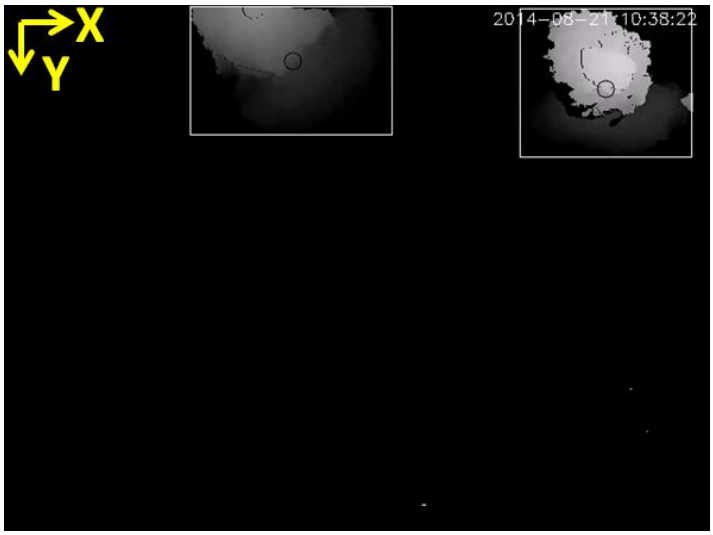


Figure 3.12: An example of recorded depth image frame with 2 person detected and current time is displayed at the right top corner. The original point is at frame left top corner. The relatively position are saved in 'csv' file and shown in Table 3.1.

3.5 Summary

This chapter presents the development of the hardware and software component of CATS. A Microsoft Kinect with image and infrared depth sensor was used in conjunction with a portable laptop for the CATS hardware. The software was written in Microsoft Express C++ with OpenNI, 'OpenCV' and Kinect SDK. The images recorded using the Kinect were processed and filtered to obtain images for data storage in this application.

In the next chapter, the performance of this system is tested in a laboratory environment. Several tests carried out by test subjects will simulate movement in the CATS tracking area. The main goal is to validate and quantify the accuracy and precision of CATS. In addition, preliminary metrics to evaluate workload in the tracking area are also developed and presented.

Chapter 4: CATS Performance in an Experimental Environment

4.1 Introduction

The design and development of the hardware and software system for clinical activity tracking system (CATS) were presented in Chapter 3. CATS is specifically designed to monitor and track clinical activity at the patient bedside. The system is first tested in a laboratory setting to simulate actual conditions where CATS will be implemented for clinical validation. In addition, this setup enables specific system variables, such as detection depth and blob size setting, mentioned in Chapter 3 to be tested for reliability and robustness.

This chapter presents two important metrics that can be used to evaluate ICU nursing activity. These metrics are: 1) distance travelled within area; and 2) dwell time or time spent in area. The first assesses time in clinically relevant activity, and the second the time using specific device or therapeutic system. In addition, the experimental sets up one methodology, as well as the results found investigating the performance, robustness, and reliability of CATS are presented. The results presented in this Chapter will be used to justify the application of CATS in a clinical setting.

4.2 CATS nursing activity evaluation metrics

For CATS, two evaluation metrics were developed to monitor and quantify patient-nurse interaction:

1. Distance travelled:

This first metric is the relative distance travelled by the nurse within the monitored area. This distance is measured from a fixed point, as illustrated in Figure 4.1. This fixed point can be set at the corner of the patient bedside or any other relevant location. With this specific location, a smaller distance between the nurse and patient bedside suggests that the nurse is near to the patient and taking care of the patient or working on a more intensive clinical activity. If the measured distance is larger, and remains so for several seconds, it can be an indication that the nursing activity is focused on data recording, or other less intensive activities.

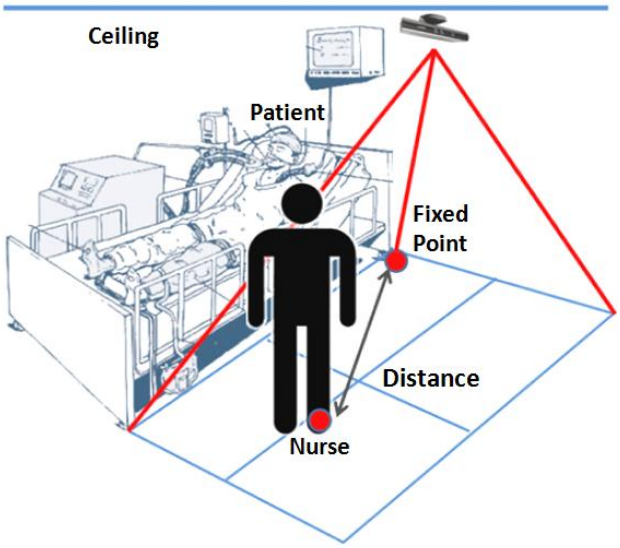


Figure 4.1: The distance between each nurse and the fixed point

2. Dwell time:

The second metric is dwell time. Dwell time is recorded as the time when a nurse is not moving in the area of interest and thus standing in a fixed position while performing clinical tasks. By retrospectively analysing the dwell time, the relationship between nursing activities [78, 87] and patient condition can be determined. Hence, for patients with different illness scores, it should become possible to quantify the labour involved in taking care of each

patient. Equally, for patients with the same illness scores, it is possible to determine why, or if, they need different amounts of care, and thus, which conditions or disease states require more nursing staff.

4.3 System evaluation methodology

CATS has several system variables. These variables can be fine-tuned based on the location of its application, as well as the object of interest within the testing areas. These variables include: 1) detecting depth range, which determines the detection distance; 2) object size filter, which determines the size of blobs being recorded; 3) blob distance grouping filter, which controls combining several overlapping blobs into one; 4) recording time interval, which controls the frequency at which blobs are recorded; and 5) maximum recorded blobs, which controls how many blobs each sensor can contain. In this experiment, the performance of CATS with different system variable settings is evaluated. A five-step experimental procedure was used to test the system performance and consistency of each set of variables:

1) A test subject with the height of 1.74 m enters into the detection area to obtain an optimal infrared depth sensing range. This selection was done based on the median height of the population [189]. Under this procedure, the CATS total area detection range is also calculated.

2) Different blob size filters are tested in the detection area to obtain the optimal filtering range settings.

3) Using the optimal system setting, test subjects perform different walking patterns that were designed to test system accuracy, repeatability and robustness.

4) Test subjects with different heights enter the detection area for testing. Three candidates with different heights of 1.74 m, 1.52 m and 1.90 m were included in the study to span the likely height range [189], to test robustness to variation in height.

5) CATS is finally tested with multiple test subjects entering the detection area simultaneously. This condition is used to simulate multiple nurses assisting each other in an ICU bed space.

4.3.1 Walking patterns for single candidate tests

The tracking area is divided into 4 zones, and labelled A, B, C and D. In the tracking area, 9 distinct feature points are set, as numbered in Figure 4.2. The 9 feature points are used to help indicate where the test candidate should stop for each pattern tested. The fixed point is at the top right corner, and the original point of coordinate system is at the left bottom corner. The test candidate with 1.74 m height performed four different walking patterns, as shown in Figure 4.3. Each walking pattern was repeated 5 times. The time spans in each region indicate time intervals when the person stopped walking at a specified location and was assessed as dwell time.

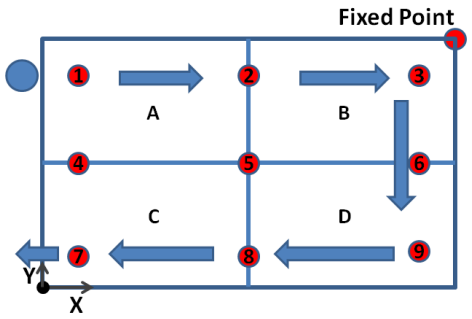


Figure 4.2: The tracking area is divided into 4 zones with 9 designated feature points.

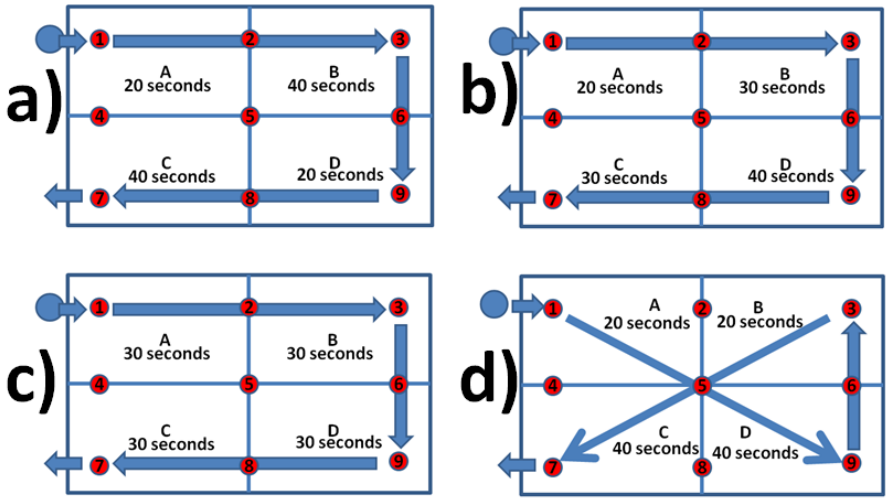


Figure 4.3: Different motion paths and timing for the single candidate tests. The time in each region indicate times where the person stopped walking and assessed as dwell time.

4.3.2 Walking patterns for two candidate tests

The walking pattern for two test candidates is shown in Figure 4.4. The first candidate was 1.90 m tall and the second candidate was 1.67 m tall. The results show the robustness of CATS for two people simultaneously in the space. Given the area size, it is unlikely that three people will use it at one time. However, the system is general enough to perform tracking for more people.

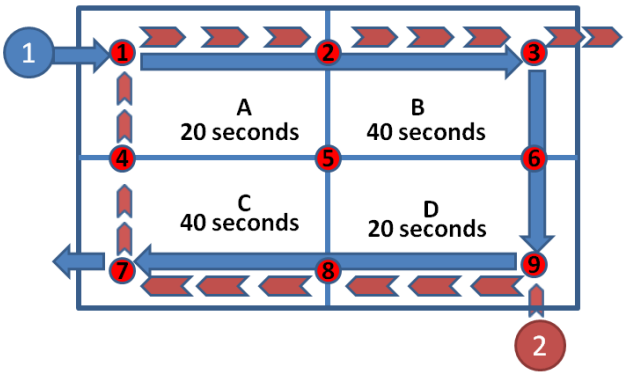


Figure 4.4: The walking pattern designed for two people. The first candidate was 1.90 m tall and the second candidate was 1.67 m tall. Person 1 stopped at points 1-3-9-7 for 20-40-20-40 seconds, and Person 2 stopped at points 9-7-1-3 for 20-40-20-40 seconds.

4.3.3 Testing process for determining the optimal system setting

The test regime was designed as follows:

1) Setting the system maximum and minimum infrared sensor depth: a test candidate with 1.74 m height performed the walking pattern in Figure 4.3(a). The pattern was walked as consistently as possible and dwell times were held using a stopwatch and directed by an external person. To test the system's robustness to different dwell time intervals, two different patterns in Figure 4.3(a) and Figure 4.3(c) were used.
2) Blob filter selection: combinations of filter thresholds of 5000-20000 pixels and 5500-30000 pixels were tested to find the best blob filter for the tests in Step 1.
3) Different path pattern tests: the settings obtained from steps 1-2 were used to test all 4 patterns in Figure 4.3 and calculate the accuracy and consistency versus known dimensions and dwell times, using one test candidate with the average 1.74m height.
4) Different candidate height test: after optimisation with the 1.74 m tall person in steps 1-3, the system was tested for heights ranging from 1.50-1.90 m using the pattern of Figure 4.3(a). The results were used to adjust the Maximum Depth value that would work for the majority of the population, and this provides robustness to this variable.
5) Multiple candidates test: to test the system for multiple concurrent people, the final optimal setting was tested for the 1.67 m and 1.90 m candidate simultaneously using the patterns shown in Figure 4.4.

4.3.4 Absolute percentage error (APE) of motion tracking

The system's ability to capture motion information was assessed using absolute percentage error (APE) compared to the average distance over all iterations from the fixed point as shown in Equation 4.1:

$$\text{APE (t)} = \left\| \frac{\text{Distance(t)}-\text{Average Distance}}{\text{Average Distance}} \right\| \times 100\%, \quad (4.1)$$

where

t=Time spent in tracking area.

The Median, inter-quartile range (IQR) and 90% confidence interval (CI) of the APE are calculated. The APE (t) for 5 test iterations are then averaged. These statistical metrics, along with dwell time, assess the system's ability to accurately and robustly capture the test candidates or nurses trajectory when moving in the space.

An example of the calculation process is shown in Table 4.1. First, the system records the location of the test candidate. Then, the distance from the test candidate to a predetermined fixed point was calculated. This process is repeated for 5 iterations. Then, the average of these 5 iterations is calculated, along with APE. Finally, the 5%, 25%, 50%, 75%, and 95% percentile is generated and averaged, and the cumulative distribution is plotted.

Table 4.1: Distance to a fixed point (640,480) within 120 seconds for 5 iterations and one subject. The APE is calculated using Equation 4.1. 5%, 25%, 50%, 75%, and 95% percentile is generated and averaged.

Distance (pixel)							**APE (%)**					
Time	**Iteration**					**Avg.**	**Iteration**					**Avg.**
	1	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**	
1	511.1	488.6	494.5	503.8	527.9	505.2	1.2	3.3	2.1	0.3	4.5	
2	500.5	485.4	490.7	489.0	509.3	495.0	1.1	1.9	0.9	1.2	2.9	
3	499.8	487.7	492.6	487.9	507.6	495.1	0.9	1.5	0.5	1.5	2.5	
…..												
120	581.4	594.6	583.1	590.0	581.2	586.1	0.8	1.5	0.5	0.7	0.8	
					5th Percentile		0.96	0.41	0.25	0.26	0.28	0.43
					25th Percentile		0.99	1.96	0.82	0.81	0.89	1.09
					50th Percentile		1.06	2.59	1.27	1.35	2.05	1.67
					75th Percentile		1.13	6.33	3.08	5.31	6.53	4.47
					95th Percentile		1.16	11.15	10.55	10.81	22.45	11.22

4.3.5 Additional data processing:

After CATS recorded test candidate blobs position and corresponding time, these information are further processed using Matlab R2014a (Version 8.3) [203-207]. The system identifies the number test candidates in each test and locates the data accordingly. If any blob remains in a region for 5 or more seconds, system starts to store blobs positions and corresponding times, and any blobs appeared shorter than 5 seconds are ignored. Figure 4.5 shows the 3-D plot of test candidate position and corresponding time, where dwell time is time spent at a fixed (x, y) position.

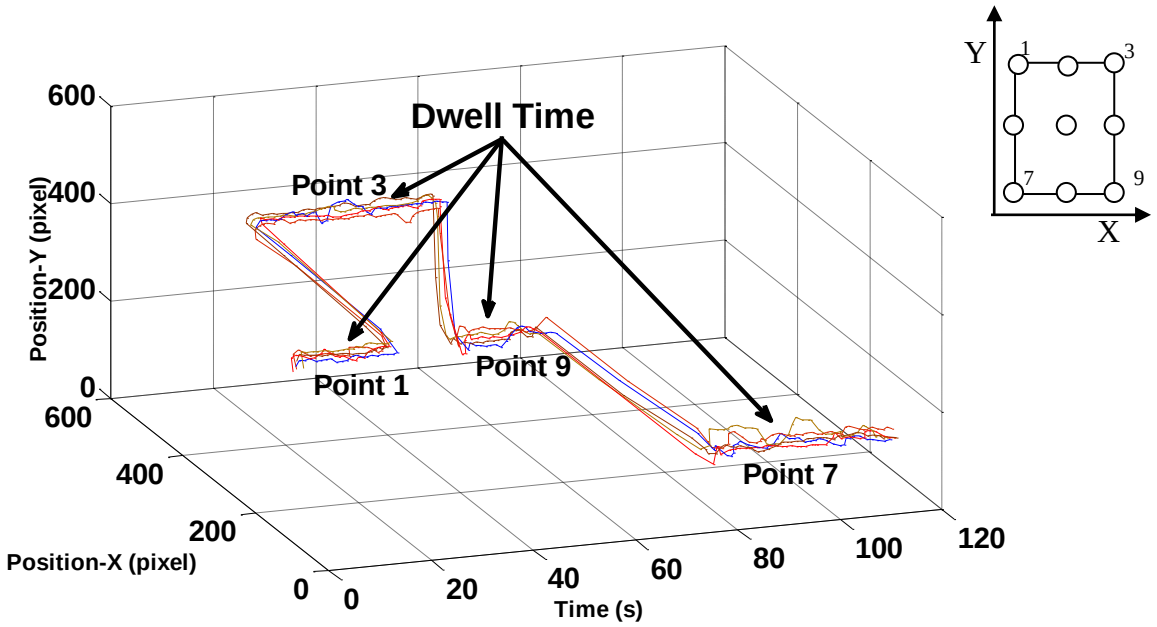


Figure 4.5: 3-D plot of test candidate centre position versus dwell time. Test candidate follow walking path in Figure 4.3(a), with 5 iterations.

4.4 Results

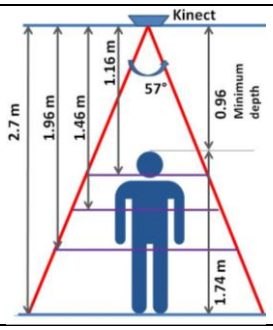
4.4.1 Test 1: finding optimal maximum and minimum depth

Area covered:

In this study, the size of the tracking area varies depending on the value of the Maximum Depth. Several combinations of minimum and maximum depth were tested. This study was

performed with a test candidate at the height of 1.74 m. Table 4.2 shows the combinations tested and their resulting total tracking area.

Table 4.2: Tracking area based on maximum and minimum depth variables

	**Candidates Body Part**	**Depth**		**Total Tracking Area (Length (m) × Width (m))**
		Minimum Depth (m)	**Maximum Depth (m)**	
	Head (0.96 m-1.16 m)	2.7 - 1.74 = 0.96	2.7 - 1.54 = 1.16	1.38 × 1.00
	Chest (0.96 m-1.46 m)	2.7 - 1.74 = 0.96	2.7 - 1.24 = 1.46	1.90 × 1.40
	Thigh (0.96 m-1.96 m)	2.7 - 1.74 = 0.96	2.7 - 0.74 = 1.96	2.30 × 1.60

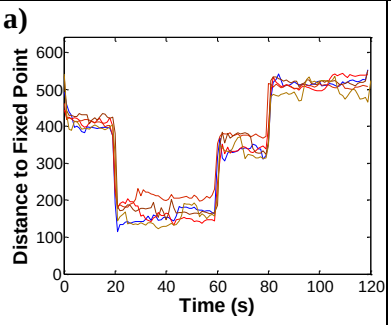
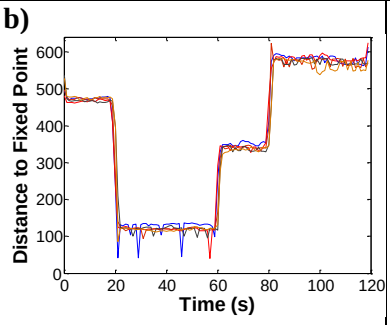
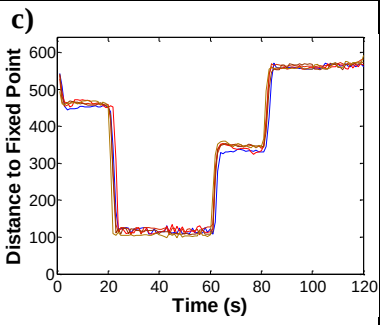
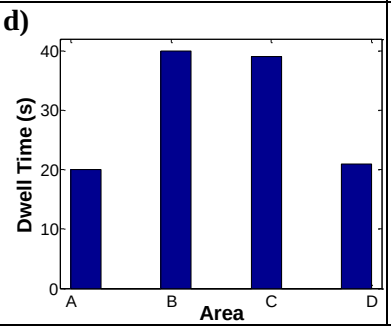
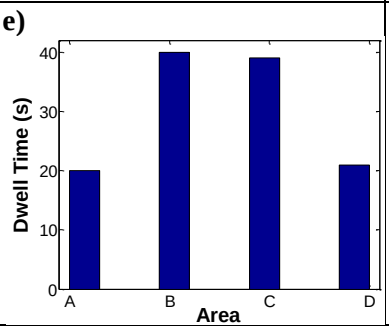
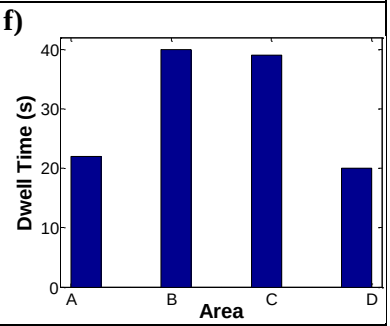
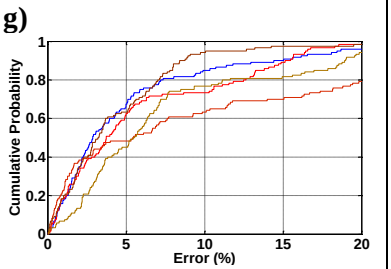
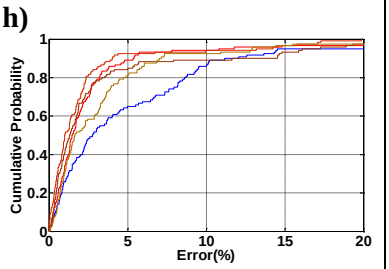
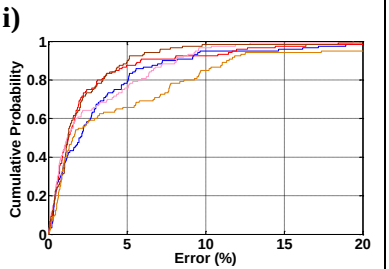
Comparison between head, chest and thigh detection

In these 3 infrared depth settings and with respect to total tracking area, the test candidate performs a walking pattern for 5 iterations. The corresponding result is shown in Table 4.3. Table 4.3(a-c) shows the distance travelled using different levels of depth in the body for detection. The Y-axis indicates the distance from the fixed point A measured pixels. Each test-iteration is represented by an individual line. Table 4.3(d-f) shows the dwell time of the first iteration. Table 4.3(g-i) shows cumulative distribution of the errors from 5 trials, the average Median, IQR and 90% CI of Error are also presented. The results in Table 4.3 show that tracking chest and thigh are comparatively more robust than tracking the head based on Maximum Depth, which means that the maximum depth should be greater than 1.46 m. However, tracking at thigh height begins to reach patient bed height range, so may result in additional errors.

Detecting the head involves relatively higher movement noise even when the candidate is standing still. There are several possible reasons behind this added error or noise. The

candidate's head is relatively nearer to the Kinect infrared sensor camera, and thus even slight movements are detected and may cause unwanted noise. In addition, the Kinect uses an infrared sensor. Thus the reflective properties of the detected surface can play an important role. The surface of the human head is more variable compared to the larger smooth surfaces, such as the shoulders. Finally, there is often or always small head motion that may cause further noise. Thus, tracking head surface will result in higher noise as shown in Table 4.3(a).

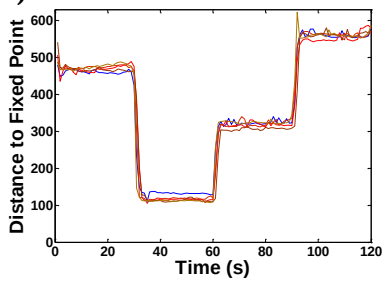
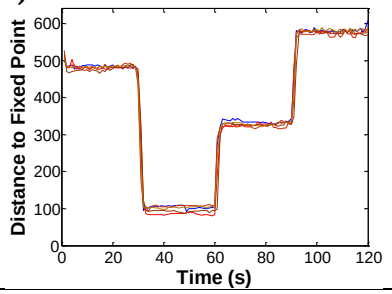
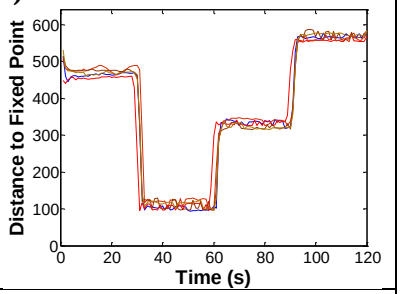
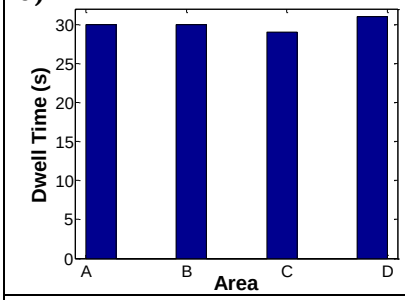
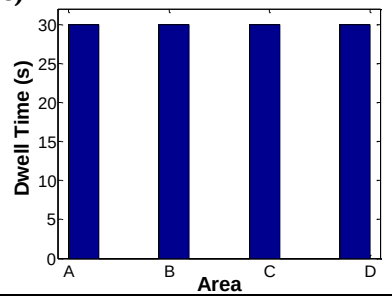
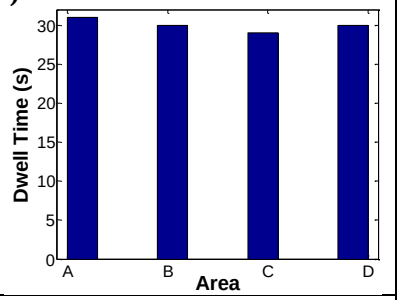
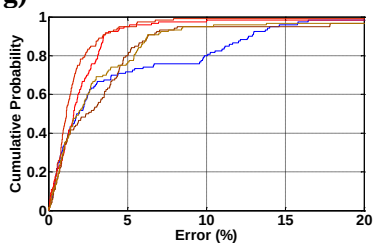
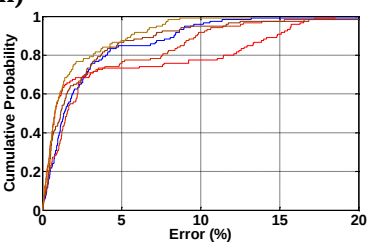
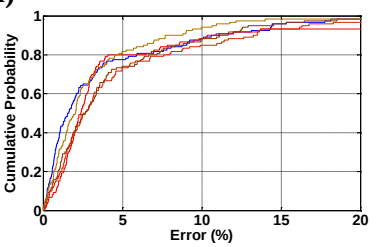
Table 4.3: Test 1: The consistency of tracking with different maximum depth. The walking pattern used is shown in Figure 4.3 (a), with the Fixed Point at top right corner, as shown in Figure 4.2. In plots a) - c), each line shows the distance to the fixed point for different iterations; plots d) – f) show the dwelling time of the first iteration; and plots g) – i) show the error CDF over 5 iterations.

Depth: 0.96-1.16 m(Head Detection)	Depth: 0.96-1.46 m(Chest Detection)	Depth: 0.96-1.96 m(Thigh Detection)
a) 	**b)** 	**c)** 
d) 	**e)** 	**f)** 
g) 	**h)** 	**i)** 
Median=4.15; IQR=[1.68,9.95]; 90%CI=[0.32,19.48]	Median=1.64; IQR=[0.70, 3.90]; 90%CI=[0.18, 13.61]	Median=1.45; IQR=[0.59, 4.40]; 90%CI=[0.14, 11.11]

Comparison of different minimum depths

Chest detection is found to be more reliable during motion tracking, and the Maximum Depth is thus fixed as 1.46 m. With this Maximum Depth threshold, the Minimum Depth value was tested at 0.66 m, 0.96 m and 1.26 m respectively. Recall that these distances are down from the 2.7 m high ceiling. In this iteration, the walking pattern in Figure 4.3(c) was used to test system robustness for different dwell times. The resulting motion paths and dwell time are shown in Table 4.4 for all cases.

Table 4.4: Test 1: The consistency of the tracking with different minimum depth. The walking pattern used is shown in Figure 4.3 (c), with the Fixed Point at top right corner. In plots a) - c), each line shows the distance to the fixed point for different iterations; plots d) – f) show the dwelling time of the first iteration; and plots g) – i) show the error CDF over 5 iterations.

Depth:0.66-1.46 m (1.24-2.04 m above floor)	Depth:0.96-1.46 m (1.24-1.74 m above floor)	Depth:1.26-1.46 m (1.24-1.44 m above floor)
a) 	**b)** 	**c)** 
d) 	**e)** 	**f)** 
g) 	**h)** 	**i)** 
Median=1.78; IQR=[0.73, 4.05]; 90%CI=[0.16, 8.11]	Median=1.12; IQR=[0.52, 4.11]; 90%CI=[0.08, 10.57]	Median=2.24; IQR=[1.09, 4.48]; 90%CI=[0.21, 17.33]

It was found that the different Minimum Depths tested all yielded less error comparing to Table 4.3 (a). It can be concluded that minimum depth parameter has relatively little impact on the tracking ability of the system. Based on these results, the Minimum and Maximum Infrared Depth settings can be set at 0.96-1.46 m to achieve optimal and robust motion tracking.

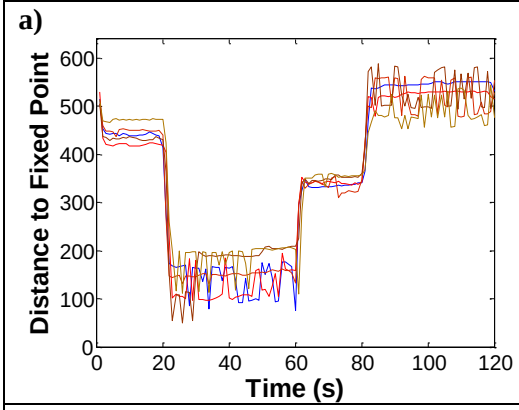
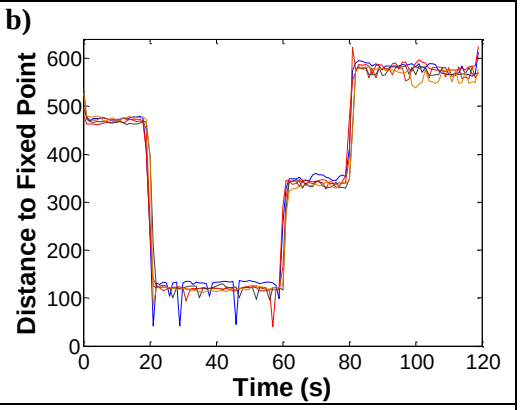
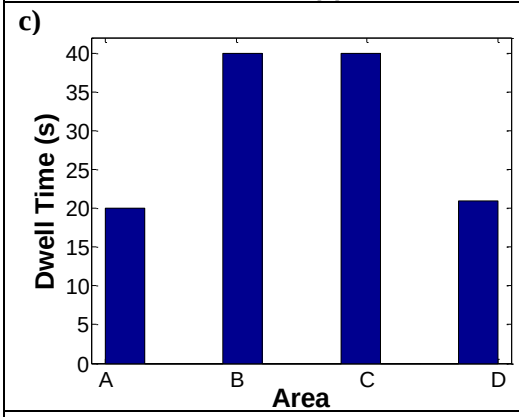
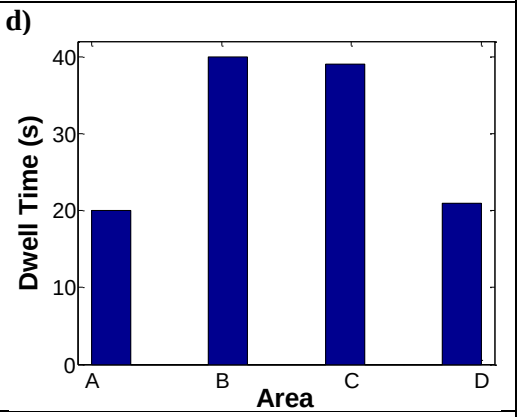
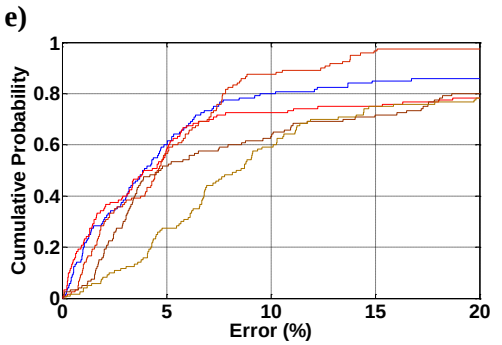
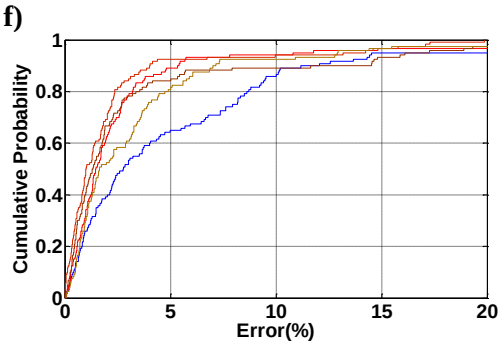
4.4.2 Test 2: different blob filters

The walking pattern in Figure 4.3(a) was used to obtain the blob filters. Table 4.5 shows the motion tracking and dwell time using different blob filters of 5000-20000 pixels and 5500-30000 pixels respectively. It was found that setting the minimal value at the 5000 pixel threshold was able to exclude blobs similar to taller candidate's head size, while a threshold of 30000 could readily include a taller candidate's shoulder size. Thus, this range was used.

It was also found that the blob size significantly influences the motion tracking. The optimal blob filter size used in this study was determined using Equation 3.3 and heuristic methods in testing various pixel combinations. A filter of 5500-30000 pixels showed a significantly more robust result than a filter of 5000-20000 pixels, which is supported by the results in Table 4.5.

From the results above, the Maximum and Minimum Depth was set to 0.96-1.66 m from the ceiling, and the blob filter size was set to 5500-35000 pixels. The increases in maximum depth from 1.46 m to 1.66 m and maximum blob size threshold from 30000 to 35000 was to allow the system to track a wider range of people. The settings are thus the most general and robust, while providing good accuracy for distance and dwell time.

Table 4.5: Test 2: The consistency of tracking with different blob filter. The walking pattern used is shown in Figure 4.3 (a), with the Fixed Point at top right corner. Plots a) and b) show distance from the fixed point for each iteration; plots c) and d) show the dwelling time of the first iteration; and plots e) and f) show the error distributions.

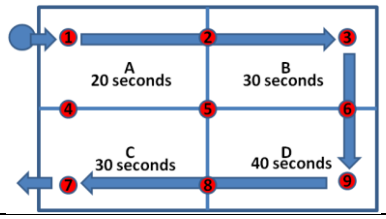
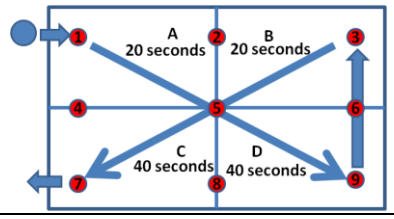
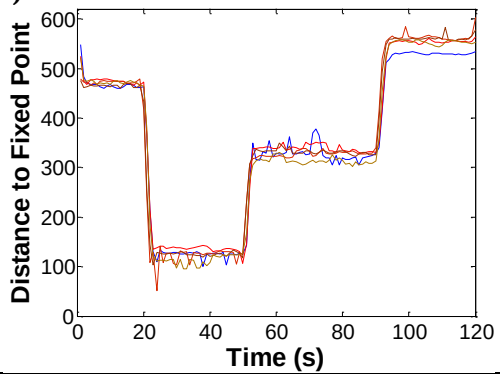
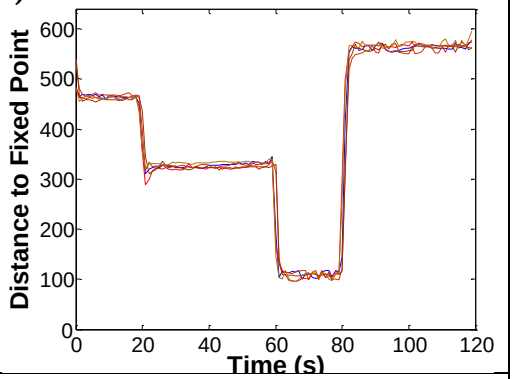
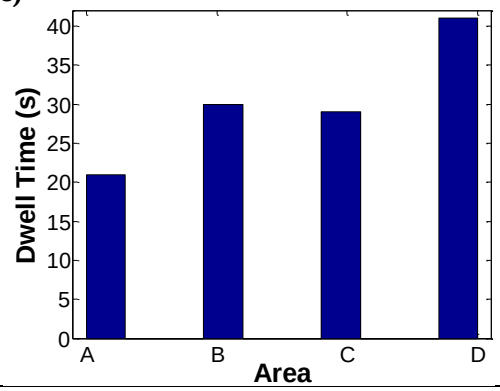
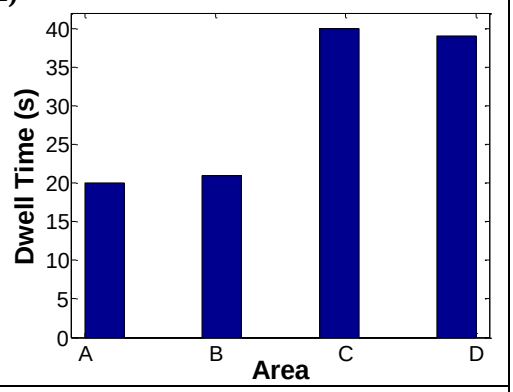
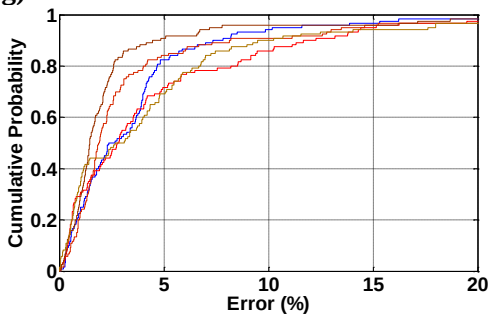
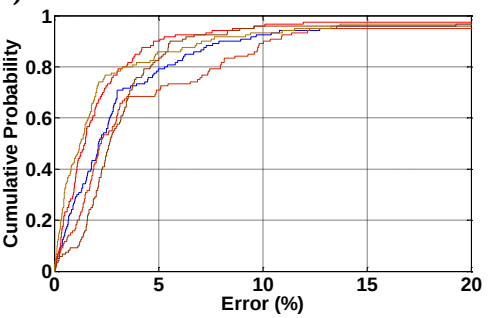
Blob Filter: 5000-20000 Pixels	Blob Filter: 5500-30000 Pixels
	
	
	
Median=5.14; IQR=[2.29, 12.01]; 90%CI=[0.78, 31.65]	Median=1.64; IQR=[0.70, 3.90]; 90%CI=[0.18, 13.61]

4.4.3 Test 3: different walking paths

Pattern A from Figure 4.3(b) and Pattern B from Figure 4.3(d) were used to compare the consistency of different walking paths, and the results are shown in Table 4.6. The results

demonstrate the ability of CATS motion tracking to adapt to different walking patterns. It is thus robust to pattern with the previously determined settings.

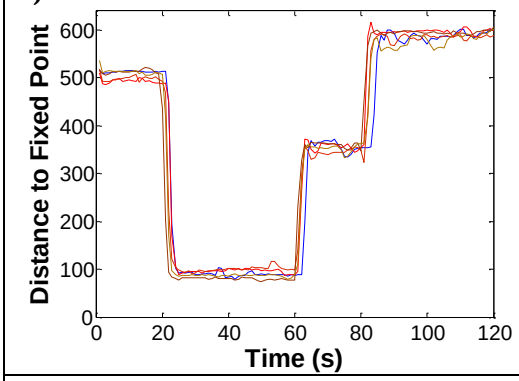
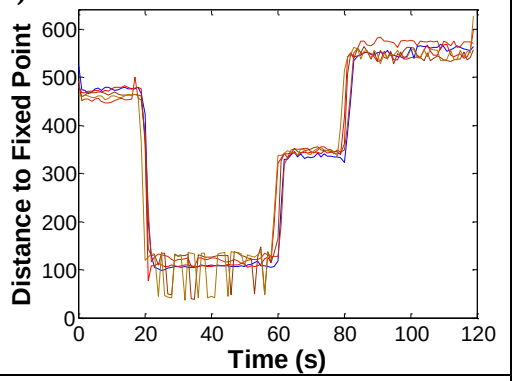
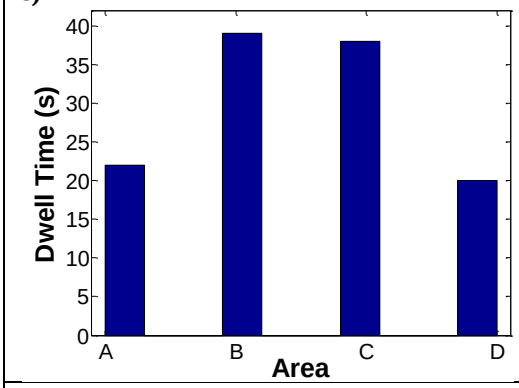
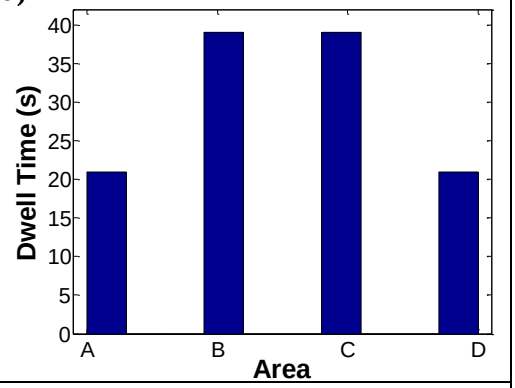
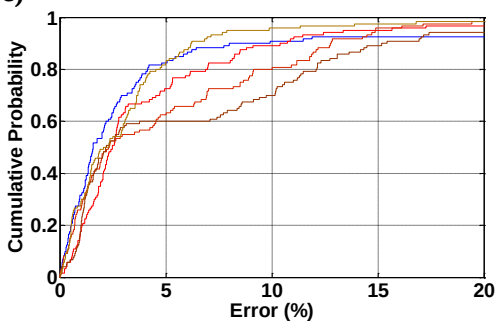
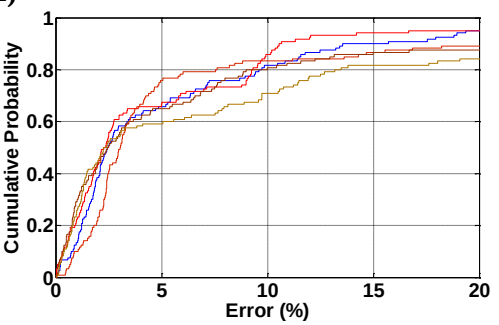
Table 4.6: Test 3: The consistency of tracking with different paths.

Path Pattern A (Figure 4.3(b))	Path Pattern B (Figure 4.3(d))
a) 	**b)** 
c) 	**d)** 
e) 	**f)** 
g)  Median=2.30; IQR=[0.72, 4.25]; 90%CI=[0.23, 12.61]	**h)**  Median=1.07; IQR=[0.46, 1.91]; 90%CI=[0.10, 8.23]

4.4.4 Test 4: different candidate heights

The walking patterns in Figure 4.3(a) were used to test system ability to capture motions of test candidates with different heights and thus ensure robustness to this variable. The results for the two different candidate heights of 1.52 m and 1.90 m are shown in Table 4.7.

Table 4.7: Test 4: The consistency of tracking different height using walking patterns from Figure 4.3(a).

Candidate's height: 1.52 m	Candidate's height: 1.90 m
a) 	b) 
c) 	d) 
e) 	f) 
Median=2.14; IQR=[0.92, 6.42]; 90%CI=[0.21, 16.38]	Median=2.52; IQR=[1.30, 8.03]; 90%CI=[0.29, 33.41]

It was found that for one of the test-runs, the 1.90 m candidate had much higher noise or error compared other runs. This result is due to the taller candidate being nearer to the Kinect sensor, and thus any slight movement of the candidate resulted in added noise and the located centre of the blob. However, of the 5 test-runs conducted by the 1.90 m candidate, only one test had increased noise. The position of the 'noisier' run is easily distinguishable and thus its impact is also reduced.

4.4.5 Test 5: multiple candidates tracking

Table 4.8 shows the result for two candidates simultaneously walking the pattern in Figure 4.4. The candidates were 1.90 m and 1.67 m in height. Table 4.8 clearly shows the system's ability to track two candidates simultaneously. In addition, it was able to differentiate the path of each candidate clearly, and capture their respective dwell times.

4.5 Discussion

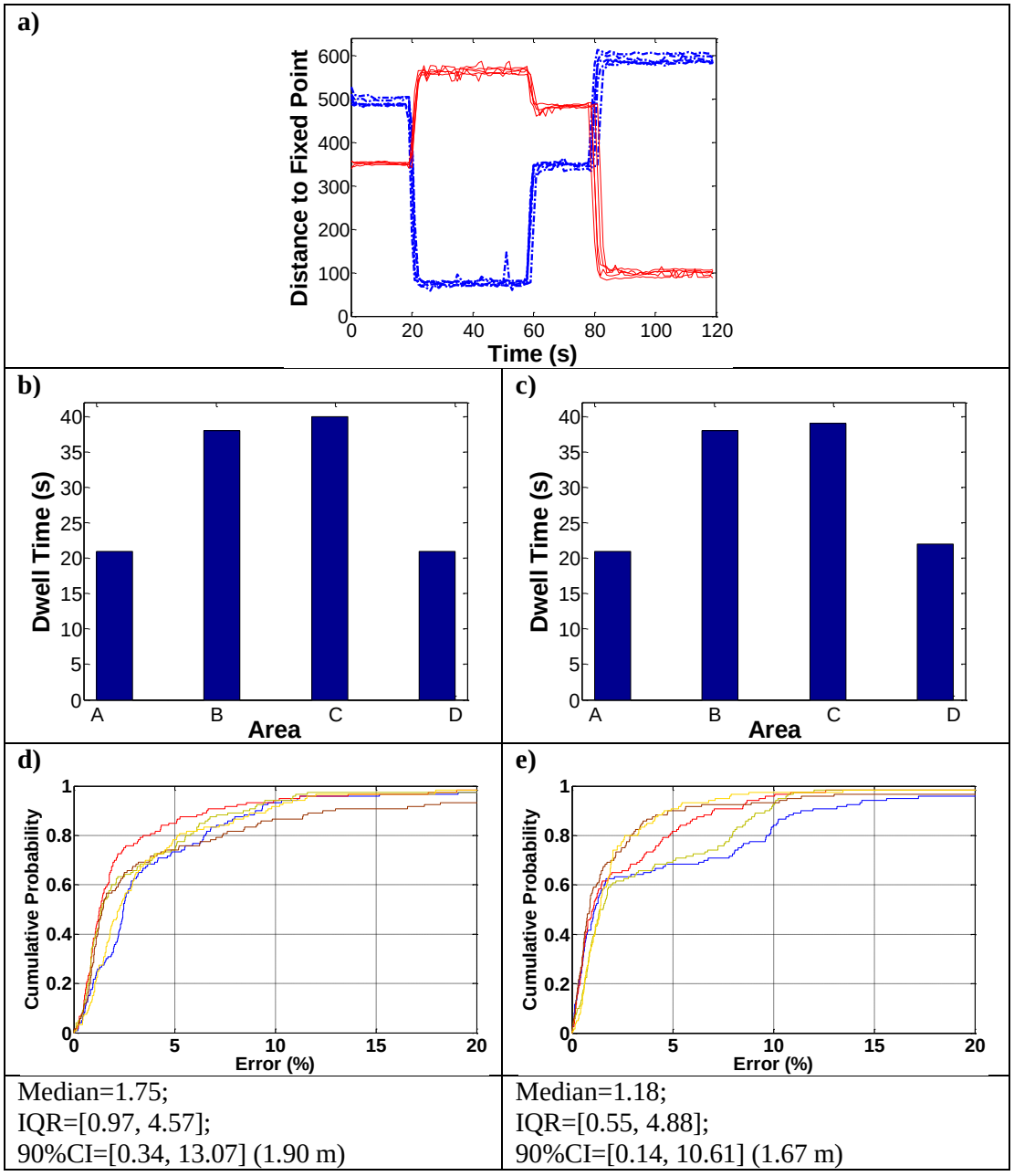
4.5.1 System mounting and area of interest

These experimental validation tests have shown that CATS can be used to accurately track test candidate motion and dwell time inside the tracking area. The system is mounted on the ceiling, reducing interruption to staff movements and is thus entirely non-invasive. Another significant advantage of CATS is that no image or identifying data was stored, protecting nurse and patient privacy, which can impact ICU working environments [105].

As found in Table 4.2, the system can cover an area larger than the 1.90 m × 1.40 m actual patient bedside area, where most nursing and clinical therapeutic activities occur. The Kinect was installed 2.7 m above the floor, the same height as the Christchurch Hospital ICU ceiling.

Under this circumstance, different experiments were designed to find the best settings that are robust to a full range of possible nurse heights, sizes, numbers, and motion patterns.

Table 4.8: Test 5: multiple candidates monitoring using walking pattern from Figure 4.4



Median=1.75; IQR=[0.97, 4.57]; 90%CI=[0.34, 13.07] (1.90 m)	Median=1.18; IQR=[0.55, 4.88]; 90%CI=[0.14, 10.61] (1.67 m)

Different Maximum and Minimum Depths were tested, as shown in Table 4.3, and it was found that 1.66 m from the ceiling (2.7 m -1.04 m) was the best Maximum Depth. This depth

(1.04 m above the floor) is below most people's chest height. Using these setting, the blobs are large enough to be continuously tracked consistently.

In Table 4.5, it was found that 5000 pixels is the optimal minimal threshold to filter out blobs that are similar in size to the head. The reason behind filtering out blobs that are smaller than 5000 pixels is that, occasionally, the blobs of head and shoulder are detected as two separate people, as shown by in Figure 4.6. The optimal maximum blob threshold was found to be 30000 pixels, which includes most body sizes and possible gestures. Finally, the range of 5500-35000 was chosen as the blob filter thresholds to support a wider range of candidates' heights. If the height of ceiling changed, the settings can be changed to compensate for the change.

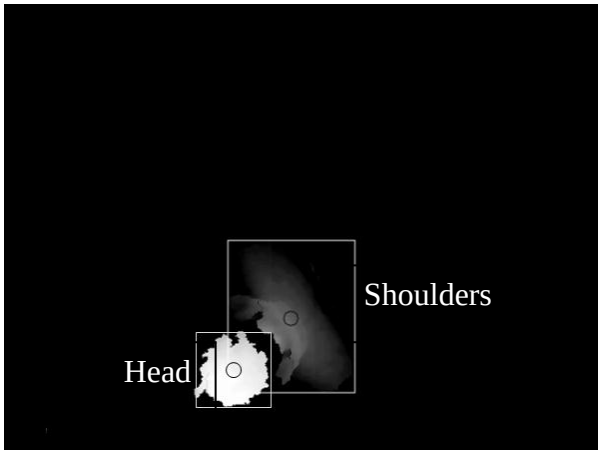


Figure 4.6: When people bend over, shoulder and head could be detected as 2 separate blobs. Blob size filter helps eliminating objects too big or too small to be a human, while blob distance filter helps combining nearby blobs into one.

Using these setting, CATS was able to detect different walking patterns, people of different heights, as well as multiple simultaneous candidates, as shown in the results in Tables 4.6-4.8. For people with different heights, CATS can robustly adapt to a range from 1.50 -1.90 m,

which covers at least 90% of the population. For multiple candidates, CATS is capable of identifying each person by retrospectively analysing the data and recording each person's trajectory.

In this study, two evaluation metrics were developed to monitor patient-nurse interaction. The first metric was the distance of the nurse from a fixed point. If the distance is small, it is an indication of the nurse is near to the patient and taking care of patient. If the measured distance is larger, and remains so for several seconds, it can be an indication that the nursing activity is focused on data recording, or other less intensive clinical or non-clinical activity. The distance metric can also be used to calculate the total distance the nurse has travelled. This information can be used to aid ICU bedside setup and organize the equipment around the patients to optimise space usage.

The second metric is dwell time. By retrospectively analysing the dwell time, the relationship between nursing activities [78, 87] and patient situation can be better determined. Hence, for patients with different TISS-28 (Simplified Therapeutic Intervention Scoring) scores, it is possible to know how much labour each patient needs and even what devices are adjusted most if dwell time occurs near pumps or ventilators or other specific devices. From there, in clinical testing, it is possible to calculate the total nursing requirement of an ICU, relative to the patients they have. In particular, for patients with similar severity scores [2, 86, 208-211], it may be possible to determine why they need different amounts of care, and thus which type of disease states may likely require more nursing staff and effort, leading to a more optimal allocation of available staff to patients.

4.5.2 System and testing limitations

There are several limitations of the CATS that should be addressed before clinical deployment and validation testing:

1. CATS cannot identify the person in the tracking area because of the health and privacy issue of the working area. Thus, the system tracks everyone, including non ICU staff, such as technicians and family members. This global tracking may potentially affect the data recording. However, as the occurrence of non ICU staff in the tracking area near to or at the bedside is limited, CATS can separate nursing interventions and non nursing intervention by analysing moving pattern, or, if small, these non-clinical activities might be ignored in the data over several hours or days. In particular, in Christchurch Hospital ICU, family members typically sit outside the proposed tracking area when visiting, and the tracking area can be adapted to minimize this effect.
2. It is important to note that this system is a motion tracking system and more detailed nursing activities, such as that described in the literature were not distinguishable [78, 87, 212].
3. CATS can only detect some of nursing activities because of the limitation of detection area. However, this problem can be solved through using multiple systems to cover larger areas of interest if needed. It is also important to note that nurse-patient interactions occur primarily in the area near the patient. Thus, CATS will correspond to the more ‘interactive’ area. It is proposed to use three such systems, one for each bedside, and one for the end.
4. A final limitation concerns multiple candidates tracking. The system treats each candidate blob as a person. However, if two or more people, and thus two or more blobs, get too close (less than 0.15 m), the system may combine them into one blob,

and one person. Once the blob separates again, the system can no longer determine, which blob corresponds to which candidate. However, this situation is unlikely in a clinical setting, and thus its impact to the overall result in clinical use would be negligent. Equally, clinical activity is assessed by person motion tracking, and thus it does not matter which person does what, but only the total distance and times of activity. It should thus be able to ignore this issue.

4.6 Summary

This chapter discussed the process used to test and set up CATS in an experimental environment. With the optimal system parameters, results have shown that CATS is able to track candidates of different heights, adapt to different motion paths, and identify multiple people simultaneously. CATS uses two metrics, distance and dwell time, to evaluate nurse-patient interaction. The overall system performance indicates that the system will work accurately and robustly for actual clinical usage.

In the next chapter, CATS is implemented in the Christchurch ICU to evaluate nursing time and activities at a specific bedspace. The process of ICU workspace approval, system installation, troubleshooting, and preliminary results for system validation are presented. This system is able to provide additional insight into ICU clinical resource management. More specifically, CATS attempts to determine an optimal nurse-to-patient ratio, and thus potentially to apportion the work force based on care required. This may help to prevent nurse burnout, reduce operational costs, and possibly even decrease patient mortality.

Chapter 5 CATS Setup in Clinical Environment

5.1 Introduction

CATS was tested in a simulated environment in Chapter 4 and the results showed the system is able to monitor and track subjects in the monitoring area with good precision. The system can adapt to people with different height, walking pattern, and activities performed by multiple people within the monitoring area. Compared to a simulated environment, where all activities performed are ideal and noise free, activities in a clinical environment are more complex and it may thus be much harder to gather the 'true' nursing intervention.

There are several challenges in implementing CATS in a clinical environment. First, CATS with only a single Kinect detection area cannot cover an entire ICU patient bed unit. Thus, it is necessary to use multiple Kinect units and potentially multiple computer platforms to perform parallel data processing. Second, compared to a simulated environment, not all activities occurring within a patient bed area are nursing activities. It is necessary to develop filtering algorithms to filter these non-nursing interventions or additional noise. Thus, a preliminary data gathering phase for this purpose is required.

This chapter first presents the system setup in the Christchurch Hospital ICU, the layout of the multiple Kinect sensors, and the region each Kinect covers. These details also include the process of gathering ethics approval by Health and Disability Ethics Committees (HDEC) [213] and approval of the Canterbury District Health Board (CDHB). The chapter then investigates several non-nursing interventions that could affect results for a monitoring area and the algorithm developed applied to eliminate these disturbances. Finally, the filters

developed are implemented in the system, and the performance of CATS with the specific filtering algorithm is assessed using initial results.

5.2 System setup in clinical trial and ethic approval

5.2.1 System setup

As mentioned in Chapter 4, Table 4.2, one Kinect sensor can monitor an area of approximately 1.9 × 1.4 m^2 for the ICU with 2.7 m ceiling height. Based on each of the Christchurch Hospital ICU patient bed units, at least 4 Kinect sensors are required to cover one entire bed unit. These 4 Kinect sensors are mounted onto the ceiling in one ICU bed unit, as shown in Figure 5.1.

Kinect sensors installed on the ceiling of the patient bed unit are labelled K1, K2, K3 and K4, with each unit covering a specific area, as shown in Figure 5.1. CATS detects all activity around the patient bedside, but excludes the patient bed area to protect the patient's privacy. Subjects (nurses) who entered the detection area performing clinical tasks will have their location and time recorded. Other human sized non-moving objects, such as equipment trolleys, chest radiography devices, intravenous (IV) pole, and dialysis machine, are recorded, but need to be filtered by CATS [214]. CATS requires 2 laptops, one on each side of the bed, with each controlling 2 Kinect sensors.

In this ICU bed unit, the K1 area is normally where the ventilation machine is located, as well as the heart rate monitor and medicine trolley. K3 is where the infusion pump and fluid feeds are located, as well as suction pipes. Thus, most of the nursing interventions relating to patient care occur in areas K1 and K3, such as routine delivery of medicines, adjustment of mechanical ventilation settings, providing provision, routine dressing, and patient position

changes. In contrast, areas K2 and K4 are where the patient chart is located. Activities such as recording patient 24h charts and laboratory reports, or communicating with doctors and families occur in these 2 areas.

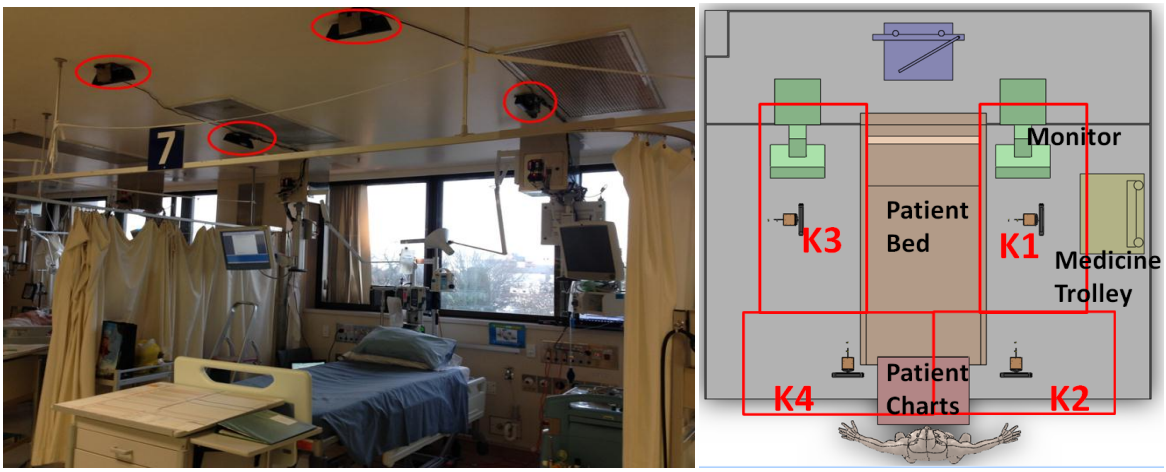


Figure 5.1: Left: The ICU unit layout with 4 Kinect sensors installed on the ceiling. Right: Top view of the areas detected by the Kinect sensors

5.2.2 Ethics approval

This research required ethics approval, even though CATS dose not record patient video footage. It has been evaluated as 'out of space' by Health and Disability Ethics Committees (HDEC). It has also been evaluated as 'No Maori Consultation Required' by TKW (Te Komiti Whakarite) [215]. In addition, Christchurch Hospital issued local authorisation form, the 'Locality Authorisation Form for HDEB', as shown in Appendix 5.1. The installation of Kinect and relative power supply socket has been approved by 'Office of Maintenance and Engineering Department, Christchurch Hospital', as shown in Appendix 5.2.

5.3 Data post-processing according to specific limitations in 4 sub-areas

In this research, a major challenge is to quantify the true direct nursing interventions in a busy ICU environment. Nursing intervention refers to those nursing activities that directly affect patient outcome, such as giving the patient medicines, adjusting ventilator or other

equipment settings, changing patient position, wound dressing, airway care, catheter care, checking patient neurological response or temperature, emptying urine bags, meal preparation, and nutrition via pump. [2, 78-80]. Nursing intervention in this research excludes nursing activities that indirectly affect patient outcome. Examples of these indirect nursing activities are interaction with doctors or other clinical staff, consulting family members, training, recoding clinical data, patient observation only, and helping other nurses at another bedspace.

To accurately calculate nursing intervention in each area, it is necessary to eliminate non-human objects, non-clinical staff, or indirect nursing interventions. Thus, there are different 'noise' sources in different areas that affect the accuracy of nursing intervention time. In K1 and K3, the 'noise' includes the bedside monitor, intravenous (IV) drop holder, and dialysis machine, as nurses occasionally place these devices in the detection region. The identifying feature of these 'noise' sources is that their position barely changes. Thus, the centre of their corresponding blob is fixed on a specific pixel. These noise sources, while not often seen, also may occur in area K2 and K4.

Another non-nursing 'noise' observation may occur from visiting family members, who normally stay near the patient bedside and barely move for long time spans. Another potential interference can occur from the movement of the curtains. Nurses close the curtains while performing tasks, such as cleaning the patient, and thus the curtain may be detected as moving blobs in the detection area.

To validate the performance of the filtering algorithm, CATS recorded an initial 67 hours of RGB video footage for over a 5 day period in August, 2014, when patient is admitted in 'Bed

7’. Blob position is recorded every second by CATS, when at least one blob is present. If no blob is present in the detection area, no data is recorded. There are several filters applied to each area to eliminate these ‘noise’ blobs. They are: 1) curtain filter; 2) non-moving object filter; 3) flash objects and short term non-moving objects filter; 4) long term multiple objects filter; 5) non-moving nurse or family member filter; and 6) overlapped area filter. After implementation of each filter, CATS generates the total nursing intervention time and corresponding heat map for comparison. For validation, nursing intervention during these 67 hours was manually calculated by checking RGB video footage. These results are compared after each filter to assess filter performance, after which RGB footage was deleted for privacy reasons.

An example of the nursing intervention time and heat map is shown in Figure 5.2. It shows the total intervention time from 12 am - 10 am and multiple nursing interventions without applying any filter. For example, from 9 am - 10 am, system detected at least 1 blob in area K2 for 3179 seconds, at least 2 blobs appeared for 1993 seconds, and at least 3 blobs appeared for 662 seconds. Figure 5.2 also shows the corresponding 1st blob probability heat map in a top down view. It shows K2 detects the bottom corner of patient bed, but patient cannot be detected because the height of patient bed is not within detection depth range. The system only extracts the 1st blob positions during these 10 hours and calculates the probability of occurrence. The same color line contours represent that it has the same probability a blob’s centre appeared on each pixel of that contour.

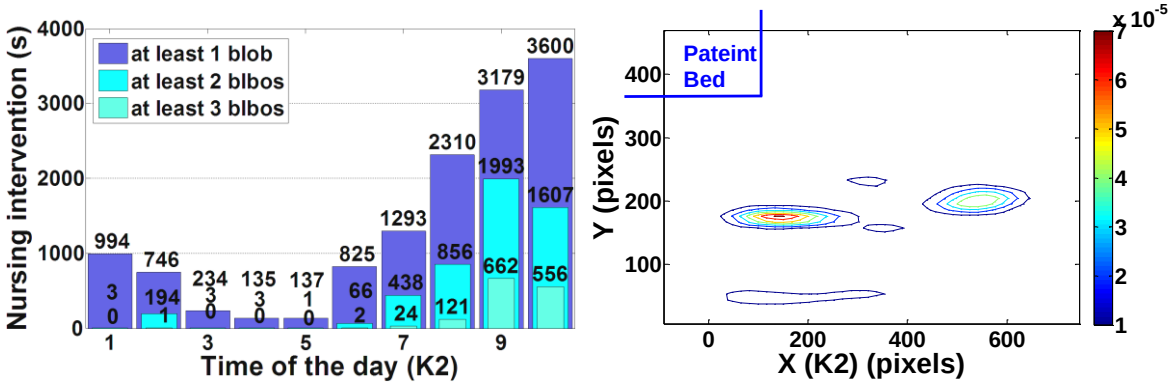


Figure 5.2: Left: multiple nursing intervention seconds in each hour without applying any filter. The X-axis is time, where '3' means from 3 am - 4 am. The Y-axis is the nursing intervention (in seconds) for each hour. Right: the corresponding nursing intervention heat map, showing the probability of a blob occurring at each position over the 12- 10 am time slot. 'Red' is the 'hottest' position, 'blue' is the 'colder' position, 'White' represents the least probability.

5.3.1 Curtain filter

In this specific bed unit at area K2, a unique regular interference is the curtain. The curtain is closed when the nurse requires some privacy for the patient. More specifically, a curtain can be 'half-closed' or 'fully closed' as shown in Figure 5.3. The curtain filter is designed to delete those blobs recognized as curtain interferences, either half closed or fully closed curtain.

1. 'Half closed curtain' filter

This filter is designed for the situation when the curtain is half closed. Normally, the curtain blob is located in one typical area (500<x<640, 150<y<230) for this bedspace. A typical half closed curtain data is shown in Figure 5.4, the first column is time, 2nd and 3rd columns are the first blob (x, y) location, which is the curtain.

a)

b)

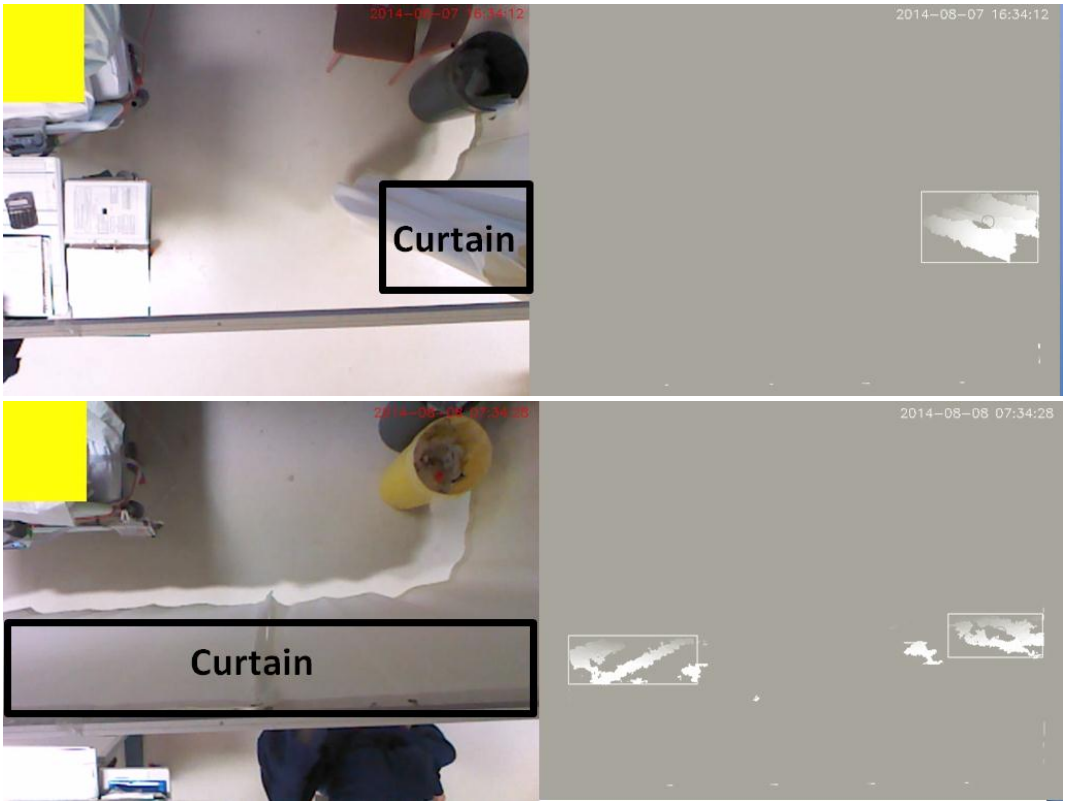


Figure 5.3: (a): Half closed curtain; (b): Fully closed curtain. The left figure shows RGB image of curtain, and the right figure shows corresponding depth image, that curtain within height range is transferred as 'noise' blob.

	Blob 1		Blob 2	
Time	x (pixel)	y (pixel)	x (pixel)	y (pixel)
74654	554	204	NaN	NaN
74655	556	207	NaN	NaN
74656	565	204	NaN	NaN
74657	585	210	NaN	NaN
74658	571	201	NaN	NaN
74659	559	203	NaN	NaN
74700	586	205	NaN	NaN
74701	563	204	NaN	NaN
74702	576	203	NaN	NaN
74703	583	207	NaN	NaN
74704	577	200	NaN	NaN
74705	585	213	NaN	NaN
74706	585	208	NaN	NaN
74707	583	205	NaN	NaN
74708	556	204	NaN	NaN

Figure 5.4: A typical half closed curtain data pattern, with 500<X<640, and 150<Y<240 for more than 3 minutes. First column is time, 2nd and 3rd columns are the first blob (x, y) location. 'NaN' represent s no instance of a second blob in this figure.

The coding procedure of to delete half closed curtain is defined:

1. Initiate ‘half closed curtain’ filter: System checks every 180 rows, if time span is no more than 3 minutes, and 80% of the rows contained blobs belonging to square (500<x<640 pixels, 150<y<240 pixels), it assumes the start of half closed curtain.
2. Check the upcoming 60 rows: If time span is less than 2 minutes and 50% of these rows contains blobs falling into square (500<x<640 pixels, 150<y<230 pixels), the ending row index added 60. Repeat this procedure until last row index is found. Half closed curtain time span is from first row recorded time till last row recorded time.
3. Within time span, replace all blobs fall into square (500<x<640, 150<y<230) with (x=0, y=0). In each row, replace non-zero blobs to the front, replace those (0, 0) with ‘NaN’. Then delete rows that only contain ‘NaN’.

In the 67 hours (4020 minutes) of RGB video footage, the ‘half closed curtain’ occurred 23 times, where the system recorded an additional of 2084 minutes of non nursing intervention. Figure 5.5 shows the result of the nursing intervention and heat map after implementing half closed curtain filter. The heat map shows that the right bottom hot spot is removed, which was due to half closed curtain occurrences.

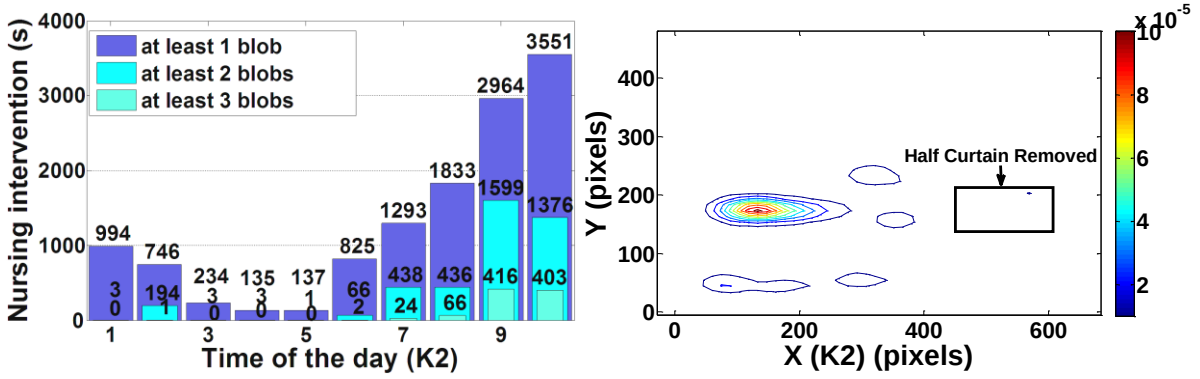


Figure 5.5: Left: Multiple nursing intervention seconds in each hour after applying ‘half closed curtain’ during 12am~ 10am. Right: The corresponding nursing intervention heat map.

However, this filter may delete nursing interventions if actual nurse interventions occurred in area (500<x<640 pixels, 150<y<230 pixels) for more than 3 minutes. Based on manual inspection of 67 hours RBG video, this phenomenon did not occur.

2. 'Fully closed curtain' filter:

The fully closed curtain filter is designed to delete blobs formed by the fully closed curtain scenario, as shown in Figure 5.3(b). For the fully closed curtain, at least 1 blob is detected in y at (150<y<220 pixels) and the positions of these blobs are not stable. Typical fully closed curtain data is shown in Figure 5.6. Fully closed curtain blobs generally stay more than 3 minutes, with y values in (150<y<220 pixels).

	Blob 1		Blob 2		Blob 3	
Time	x (pixel)	y (pixel)	x (pixel)	y (pixel)	x (pixel)	y (pixel)
73230	219	212	514	197	NaN	NaN
73231	189	207	573	211	126	46
73232	131	215	123	50	NaN	NaN
73233	192	250	568	201	NaN	NaN
73234	65	260	NaN	NaN	NaN	NaN
73235	285	178	530	202	NaN	NaN
73236	82	176	567	205	NaN	NaN
73237	100	177	570	199	NaN	NaN
73238	137	177	NaN	NaN	NaN	NaN
73239	580	207	NaN	NaN	NaN	NaN
73240	533	200	98	168	NaN	NaN
73241	580	207	100	173	NaN	NaN
73242	117	179	NaN	NaN	NaN	NaN
73243	164	173	580	203	NaN	NaN
73244	460	197	NaN	NaN	NaN	NaN
73245	562	202	NaN	NaN	NaN	NaN
73247	96	173	NaN	NaN	NaN	NaN
73248	567	205	NaN	NaN	NaN	NaN
73249	576	203	103	173	NaN	NaN
73250	567	199	115	177	NaN	NaN
73251	104	175	NaN	NaN	NaN	NaN

Figure 5.6: A typical fully closed curtain data pattern. First column is, 2nd and 3rd columns are the first blob (x, y) location, 4th and 5th columns are the second blob location. Fully closed curtain blobs generally last more than 3 minutes, with y values belong to (150<y<220 pixels). Highlighted data represents curtain movement and is removed by filtering.

To implement the fully closed curtain filter, the following algorithm is implemented:

1. Initiate ‘fully closed curtain’ filter: System checks every 180 rows. If time span is no more than 5 minutes, and 80% of these rows contains blobs belonging to Y band (150<Y<220 pixels), the first row of these 180 rows is allocated as the start of fully closed curtain.
2. Check the upcoming 60 rows: If time span is less than 2 minutes and 50% of the rows contains blobs falling into Y band (150<Y<220 pixels), the ending row index add 60. Repeat this procedure until the last row index is found.
3. Within time span, replace all blobs falling into Y band (150<Y<220 pixels) with (0, 0). In each row, replace non-zero blobs as the first blob, and replace those (0, 0) with ‘NaN’. Then delete any row that only contains ‘NaN’.

This filter has similar limitations as the half closed curtain filter, when considering a nursing intervention of more than 3 minutes in this region. Based on 67 hours RBG video, inappropriately deleted interventions occurred 4 times, with a total of 24 minutes lost (4+13+3+4=24 minutes). No ‘fully closed curtain’ occurred without being detected. This error consists constitutes 0.60% (24/4020) of the total 67 hours. The bar chart and heat map after additional ‘fully closed curtain’ filter is shown in Figure 5.7. The heat map demonstrates that the bottom hot spot is removed, and nursing position alone is now much more apparent.

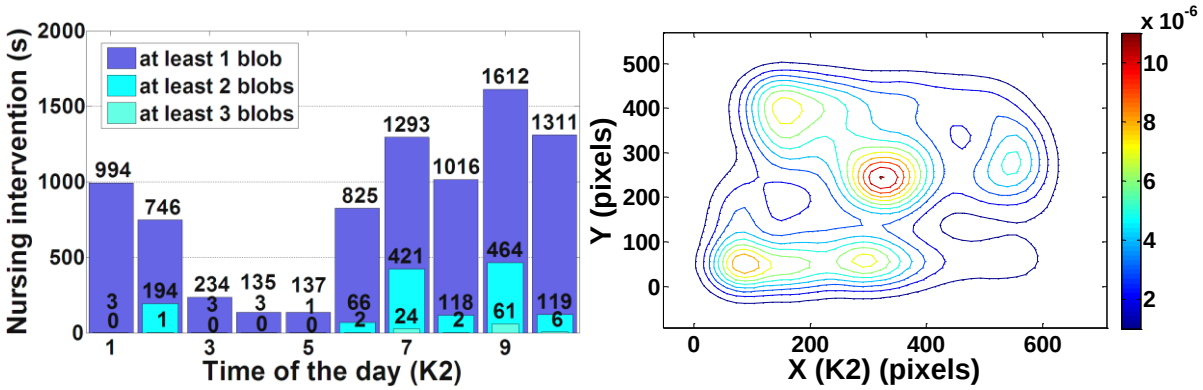


Figure 5.7: Left: multiple nursing intervention seconds in each hour after applying 'fully closed curtain' filter for a particular 12am~ 10am period. Right: the corresponding nursing intervention heat map.

A separate deletion filter for the half curtain case is implemented because this event may last for hours. Deleting all blobs falling into this Y band would wrongly delete many real nursing interventions. The difference can be very noticeable.

For example, on a particular 12am~10am (10 hours) period, the 'half close curtain' duration time was 10 hours. Deleting the entire Y band (150<Y<220 pixels) during these 10 hours would wrongly delete many real interventions. In Figure 5.8, the top row is system recorded intervention time and corresponding heat map without adding the 'half closed curtain' filter, while the bottom row adds the 'half closed curtain' filter. It shows recorded intervention time is more when adding the 'half closed curtain' filter. The heat map shows top row wrongly deleted some real intervention time.

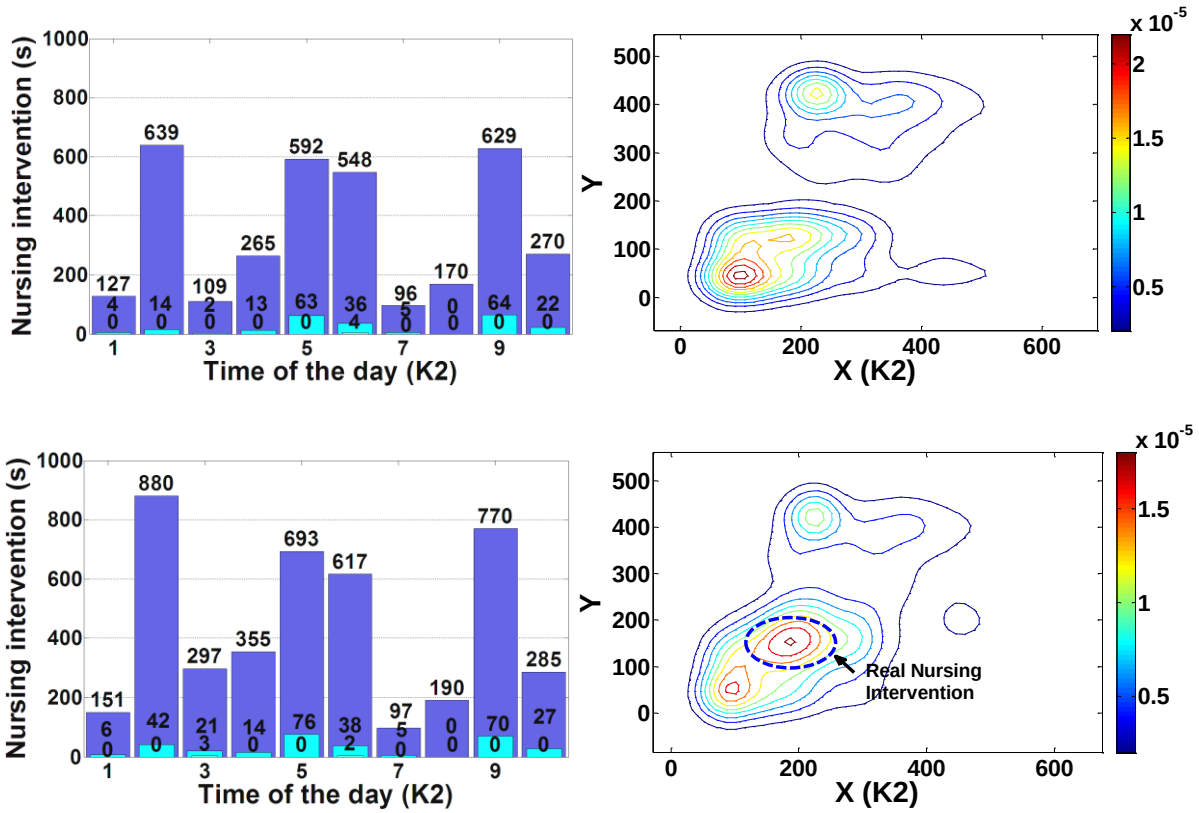


Figure 5.8: The Top row shows nursing intervention and corresponding heat map without adding the 'half closed curtain' filter on a particular 12am~10am period. The bottom row shows the same results with the 'half closed curtain' filter. The heat map shows top row wrongly deleted real nursing intervention.

5.3.2. 'Still objects' filter

In the ICU, some equipment blobs are equal or similar to human blobs. For example, the IV drop holder, dialysis machine, abdominal ultrasound machine, and X-ray machine are occasionally placed under the detection area for few minutes or hours. These non-moving objects are defined as 'still objects'. The most unique feature of still objects is their position remaining at the same pixel or within 3 pixels for more than 2 minutes. The 'Still objects' filter is designed to identify these objects and delete these motionless blobs. A typical still object is shown in Figure 5.9, and the corresponding recorded blob position data is presented. The object is the IV holder placed in K2 and the position is constant, as highlighted in Figure 5.9, at (290,270) since '012935' (1:29:35 am).

Time	Blob 1 X (pixels)	Blob 1 Y (pixels)	Blob 2 X (pixels)	Blob 2 Y (pixels)
012735	x0=503	y0=421		
012736	x0=403	y0=126		
012743	x0=395	y0=086		
012744	x0=336	y0=427		
012924	x0=466	y0=154		
012925	x0=295	y0=081		
012926	x0=276	y0=041		
012927	x0=287	y0=042		
012928	x0=293	y0=074		
012929	x0=351	y0=085		
012930	x0=407	y0=142		
012931	x0=376	y0=058	x1=444	y1=221
012932	x0=365	y0=107	x1=410	y1=307
012933	x0=345	y0=234	x1=409	y1=421
012934	x0=295	y0=268	x1=399	y1=421
012935	x0=290	y0=270	x1=424	y1=416
012936	x0=290	y0=270	x1=565	y1=309
012937	x0=290	y0=270	x1=590	y1=242
012938	x0=290	y0=270	x1=597	y1=267
012939	x0=290	y0=270		
012940	x0=290	y0=270	x1=538	y1=425
012941	x0=290	y0=270		
012942	x0=290	y0=270		
012943	x0=290	y0=270		
012944	x0=290	y0=270		
012945	x0=290	y0=270		
012946	x0=290	y0=270		

Figure 5.9: Left: A typical sill object exposed in K2 area. Right: The corresponding recorded position highlighting the unmoving blob data. The still object position normally stays at the same pixel or within 3 pixels, and generally lasts more than 3 minutes.

The procedure to delete still objects blobs is defined:

1. Initiate ‘still object’ filter: System first sorts blobs, placing closer blobs in the same column. The testing loop starts at the second row. If the first blob of the second row is ‘not moving’ (less than 3 pixels in both x and y direction comparing with the first blob in the first row), check whether the first blob in the upcoming 10 rows is 'not moving'. If yes, get the average (x, y) of the first 10 rows. Check the upcoming 120 row, if more than 85% of these rows contains at least one blobs is ‘not moving’ (less than 7 pixels in both x and y direction), it is assume these rows is the start of still object.
2. Finding the ending row index: System checks the upcoming rows, if at least one blob is ‘not moving’ in the upcoming 5 rows, the row index extends 5, till finding the last row index.

3. Within time span, replace ‘not moving’ blobs with (0, 0). In reach row, place non-zero blobs to the front, replace those (0, 0) with ‘NaN’. Then delete those rows only containing ‘NaN’.

The ‘Still objects’ filter may impose similar limitations as the fully closed curtain filter. This error occurs if nurse interventions occur at the same position, within 7 pixels in both x and y direction, for more than 2 minutes. During manual inspection, there are 4 times (approximately 14 minutes) of such filtering error. This error constitutes 0.35% (14/4020) of the entire time span, and reduces the actual nursing intervention time. Figure 5.10 shows the nursing intervention and corresponding heat map after applying the ‘still objects’ filter.

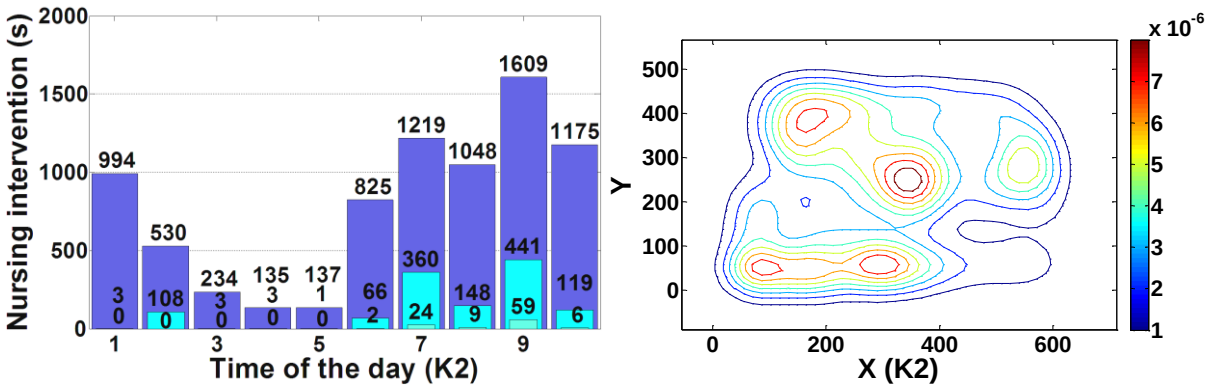


Figure 5.10: Left: Multiple nursing intervention seconds in each hour after applying ‘still objects’ filter on a particular 12am~ 10am period. Right: The corresponding nursing intervention heat map.

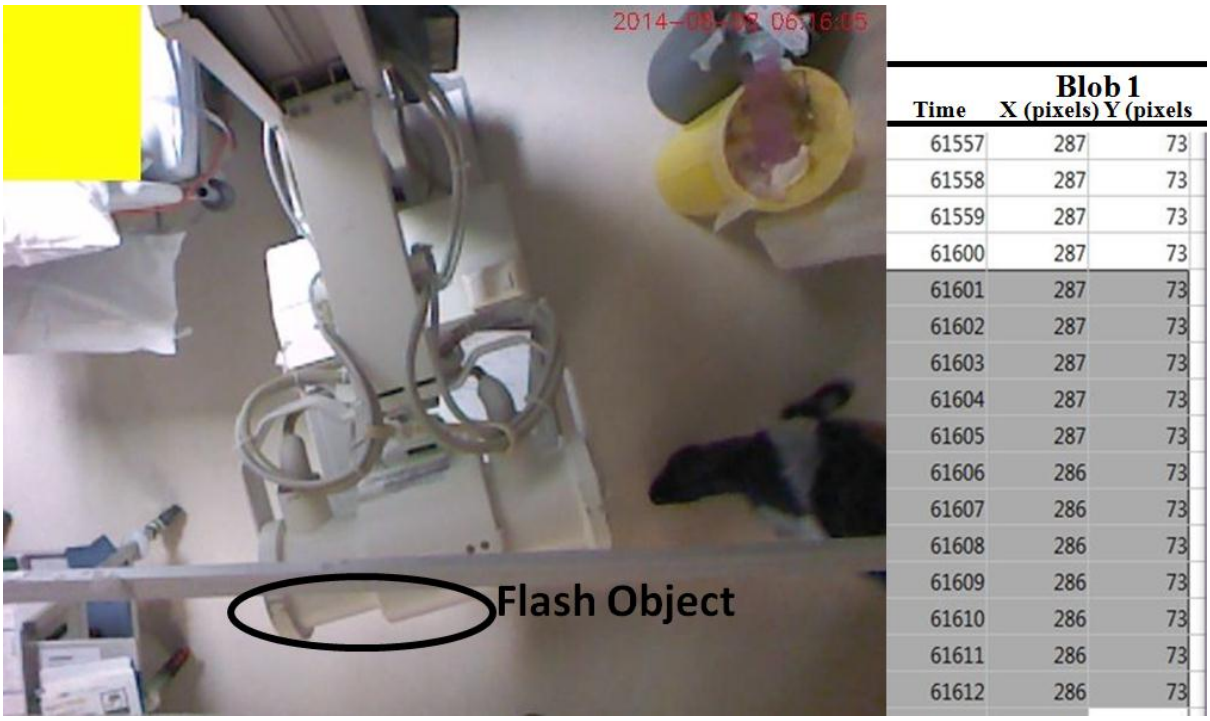
5.3.3 Flash object and short term non-moving objects filter

Two additional filters are implemented in CATS:

1) Flash objects: The centre of a detected blob tended to be less stable and disappears if blob size is similar or near to filter threshold values (5500 or 35000 pixels), or if object surface has a sharp angle from the Kinect lens, such as the curtain. These non-stable blobs are

categorised as ‘flash objects’. For these 2 situations, blobs centres can switch between 2 positions within 20 pixels. Figure 5.11 shows part of the X-ray machine is identified as ‘flash blob’, where its X position is jumping between 287 and 286, as shown in the data highlighted in Figure 5.11.

2) Short term non-moving objects: These objects refer to objects that maintain their position for short terms less than 3 minutes. The data pattern is the same as a ‘still object’, only with a much shorter period. The similarity of ‘flash objects’ and ‘short term non-moving objects’ is the very high occurrence of the same (x, y) over short periods less than 3 minutes.



Time	Blob 1 X (pixels)	Y (pixels
61557	287	73
61558	287	73
61559	287	73
61600	287	73
61601	287	73
61602	287	73
61603	287	73
61604	287	73
61605	287	73
61606	286	73
61607	286	73
61608	286	73
61609	286	73
61610	286	73
61611	286	73
61612	286	73

Figure 5.11: An X-ray machine appeared in K2 area. Circled part reaches the maximum detection depth range, thus blob x position is switching between 286 and 287, as shown at the right side. Circle part of X-ray machine is traded as flashing object.

A ‘Flashing object’ filter is designed to delete these 2 situations. The procedure is defined:

1. Within a day, find the top 20 most frequent X, X (1) –X (20). Write each blob with the same X (i) into a matrix, XMatrix (i). Considering each X (i), find the most frequent Y (i), define as (mostFrequentX, mostFrequentY). Check whether this (mostFrequentX, mostFrequentY) counts more than 40% in XMatrix (i) within less than 3 minutes. If yes, this (mostFrequentX, mostFrequentY) is either a ‘flash object’ or short term still object.
2. Replace all blobs with the position (mostFrequentX, mostFrequentY±5) by (0, 0). In each row, place non-zero blobs to the front, replace those (0, 0) with ‘NaN’. Then delete those row only contains ‘NaN’.

In this preliminary study data, there are 18.5 minutes of nursing intervention that were considered ‘flashing objects’ or ‘short term non-moving objects’. Figure 5.12 shows the nursing intervention after applying the ‘flash object and short term non-moving object’ filter.

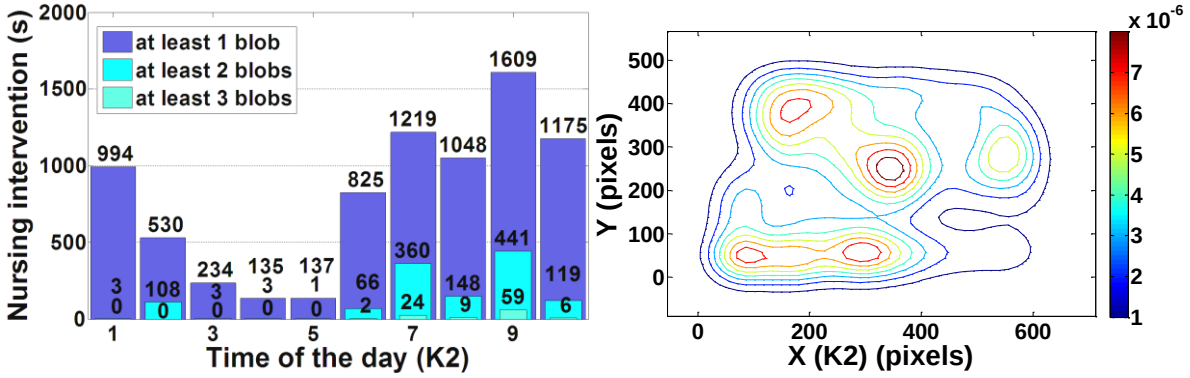


Figure 5.12: Left: Multiple nursing intervention seconds in each hour after applying ‘flash object and short term non-moving object’ filter on a particular 12am~ 10am period. Right: The corresponding nursing intervention heat map.

5.3.4 Long term multiple blobs filter

‘Long term multiple blobs’ refers to occasions when multiple blobs appeared in an area for longer than 10 minutes. In reality, ‘long term multiple blobs’ happens when a group of

researchers, doctors or family members gathered for training or consultation. These events should be filtered to more accurately therapeutic nursing interventions. A typical long term multiple blobs occasion is shown in Figure 5.13, when a group of doctors, researchers, and family members communicated about a particular patient situation.

The ‘Long term multiple blobs’ filter is defined:

1. Initiate ‘long term multiple blobs’ filter: if time span is less than 11 minutes within 600 rows, and more than 30% of the rows contains at least 2 blobs, these rows are considered as the start of long term multiple blobs.
2. Finding the last row index: if the time span of the upcoming 60 rows is less than 66 seconds, the last row index extends 60. Repeat this procedure till the very last row index is found.
3. Delete all blobs during this time span.

Figure 5.13: When group of doctors and family members gathered around patient bedside to discuss patient situation, it could add inaccurate multiple nursing intervention. This phenomenon should be filtered to reduce real nursing intervention. People’s heads are blocked out for privacy reasons.

Similar to other filters, the 'Long term multiple blobs' filter can delete useful nursing interventions. However, in this initial data, nursing interventions for longer than 10 minutes never occurred. Figure 5.14 (a) shows nursing intervention differences between applying the 'delete long term multiple blobs' filter and without this filter. Figures 5.14 (b, c) show the corresponding heat maps.

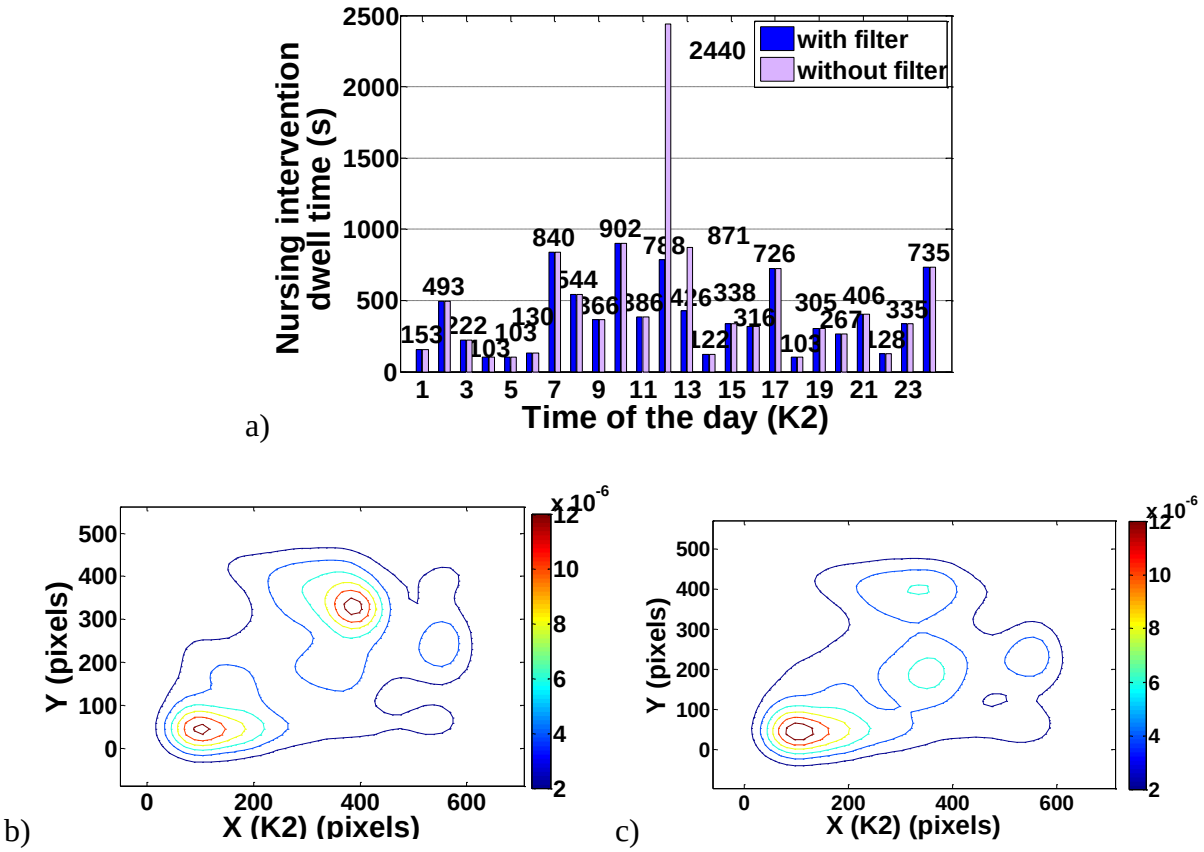


Figure 5.14: (a): Difference between applying 'long term multiple blobs' filter and without filter. At 12pm~1pm nursing intervention reduced from 2440 seconds to 788 seconds. (b): Corresponding heat map before applying filter. (c): Corresponding heat map after applying filter.

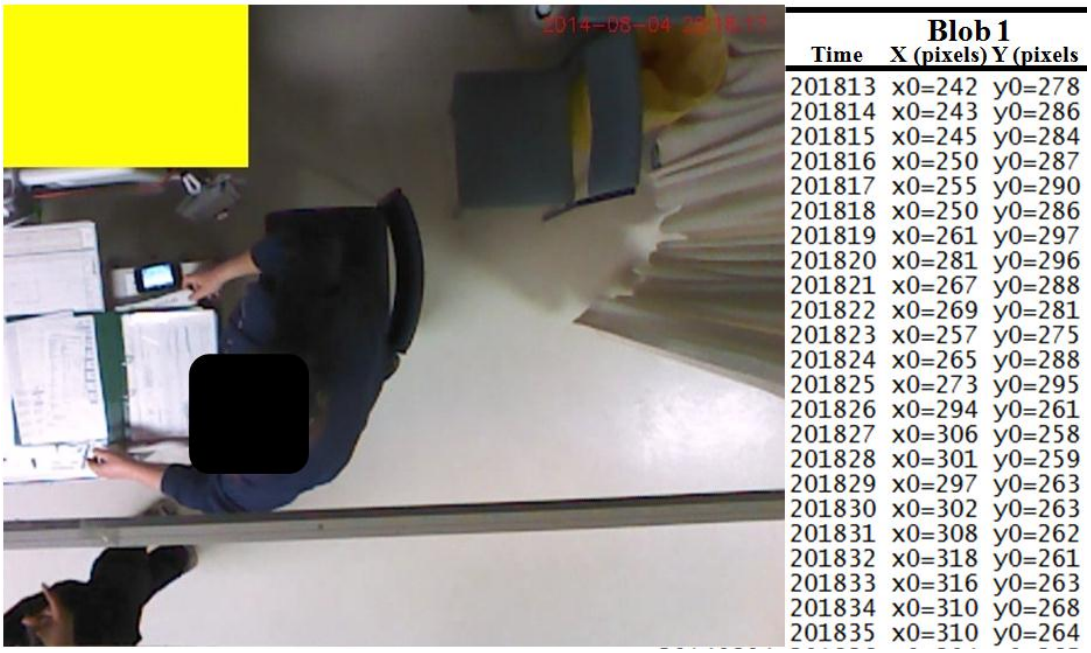
5.3.5. Non-moving nurse and family member filter

The 'Non-moving nurse or family member' filter is designed to remove 2 non-therapeutic situations:

1. When a family member stay at the same position for longer than 5 minutes.

2. When a nurse is not moving position in the detection area for longer than 5 minutes.

Occasion 1 needs to be removed, as visiting family member should not count as a nursing intervention. For occasion 2, when a nurse stays at the same position for longer than 5 minutes, they normally perform indirect nursing activities, such as communicating with other nurses, and observing patients. Non-moving nurse and family member patterns are similar to 'still objects', but move within a much larger range (60 pixels in both x and y direction). Figure 5.15 shows a typical non-moving nurse recording patient clinical charts.



Blob 1		
Time	X (pixels)	Y (pixels
201813	x0=242	y0=278
201814	x0=243	y0=286
201815	x0=245	y0=284
201816	x0=250	y0=287
201817	x0=255	y0=290
201818	x0=250	y0=286
201819	x0=261	y0=297
201820	x0=281	y0=296
201821	x0=267	y0=288
201822	x0=269	y0=281
201823	x0=257	y0=275
201824	x0=265	y0=288
201825	x0=273	y0=295
201826	x0=294	y0=261
201827	x0=306	y0=258
201828	x0=301	y0=259
201829	x0=297	y0=263
201830	x0=302	y0=263
201831	x0=308	y0=262
201832	x0=318	y0=261
201833	x0=316	y0=263
201834	x0=310	y0=268
201835	x0=310	y0=264

Figure 5.15: A nurse stands still checking patient clinical charts with her position shown at the right side. Non-moving nurse position normally stays within 60 pixels circle more than 3 minutes.

The 'Family members and non-moving nurse' filter is defined:

1. Initiate 'Family members and non-moving nurse' filter: if it takes no more than 4 minutes for 180 rows, and 90% of these rows containing at least one blob within a 60 pixels circle, it assumed the start of family member or non-moving nurse blob.

2. Check the upcoming 60 rows: if it takes no more than 2 minutes and 90% of these rows contain blobs within same circle, the last second index extended 60 rows. Repeat this procedure till last row index is found.
3. Replace all blobs in this circle within time span by (0, 0). In reach row, place non-zero blobs to the front, replace those (0, 0) with 'NaN'. Then delete rows that only contain 'NaN'.

The 'delete family members and non-moving nurse' filter may wrongly delete nursing interventions if a nurse is recording clinical data. Within the 67 hours of RBG video footage, the non-moving nurse situation occurred 4 times (18.5 minutes). The corresponding error rate is 0.46% (18.5/4020 minutes). This error could lead to recording nursing interventions that are shorter than in reality. Figure 5.16 shows nursing intervention time after applying 'Non-moving nurse or family member' filter for a particular 12am~10am period, with corresponding heat map.

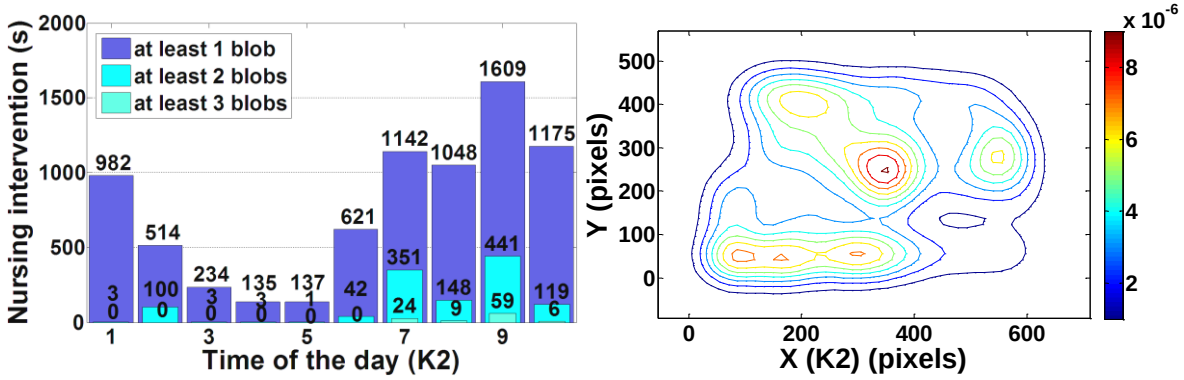


Figure 5.16: Left: Multiple nursing intervention seconds in each hour after applying 'Non moving nurse or family member' filter for a particular 12am~10am period. Right: The corresponding nursing intervention heat map.

5.3.6 Overlapped area filter

As shown in Figure 5.1, the detection area for K2 contains 2 intersecting areas with K1 and K4. The 'Overlapped area' filter is designed to avoid blobs being recorded twice in overlapped areas. To maintain the entirety of the more clinically intense K1 area, any blobs

with Y>445 pixels in the K2 area are removed. Figure 5.17 shows nursing intervention time after applying the 'Overlapped area' filter for a particular 12am~ 10am period, and corresponding heat map.

The 'Overlapped area' filter is defined:

1. Detect all the blobs that falls into X<90 pixels or Y>445 pixels, change them to (0, 0).
2. In reach row, place non-zero blobs to the front, replace those (0, 0) with 'NaN'. Then delete rows that only contain 'NaN'.

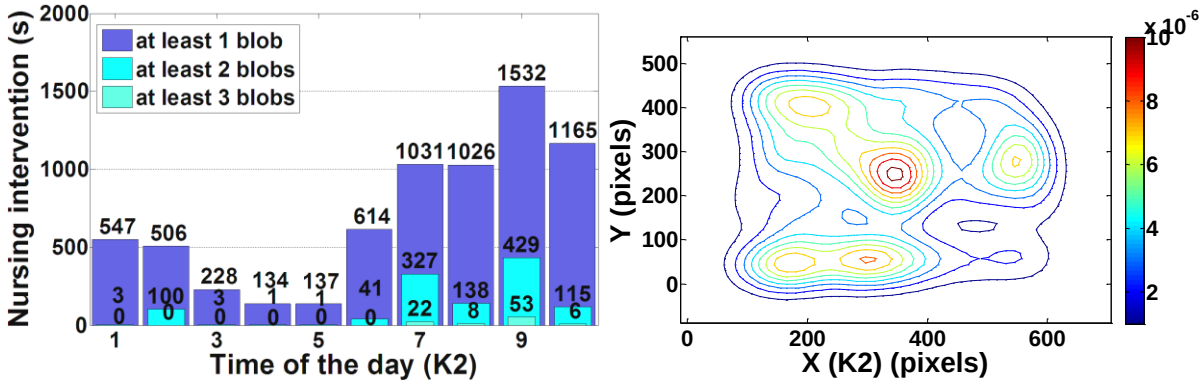


Figure 5.17: Left: Multiple nursing intervention seconds in each hour after applying 'Overlapped area' filter on day 20140808 12am~ 10am. Right: The corresponding nursing intervention heat map.

Figure 5.18 shows the flow chart of applying all the different filters. The 'half curtain' filter and 'full curtain' filter are combined as 'curtain filter' at Step 2. In some cases, tracked blobs are recorded over multiple data columns (e.g. Table 3.1), so some preliminary data reorganisation is required. Then, the system needs to delete motion from the curtain. Third, the system needs to remove 'still objects' and non-nursing staff associated movements. After all these steps the only remaining activities should be nursing action.

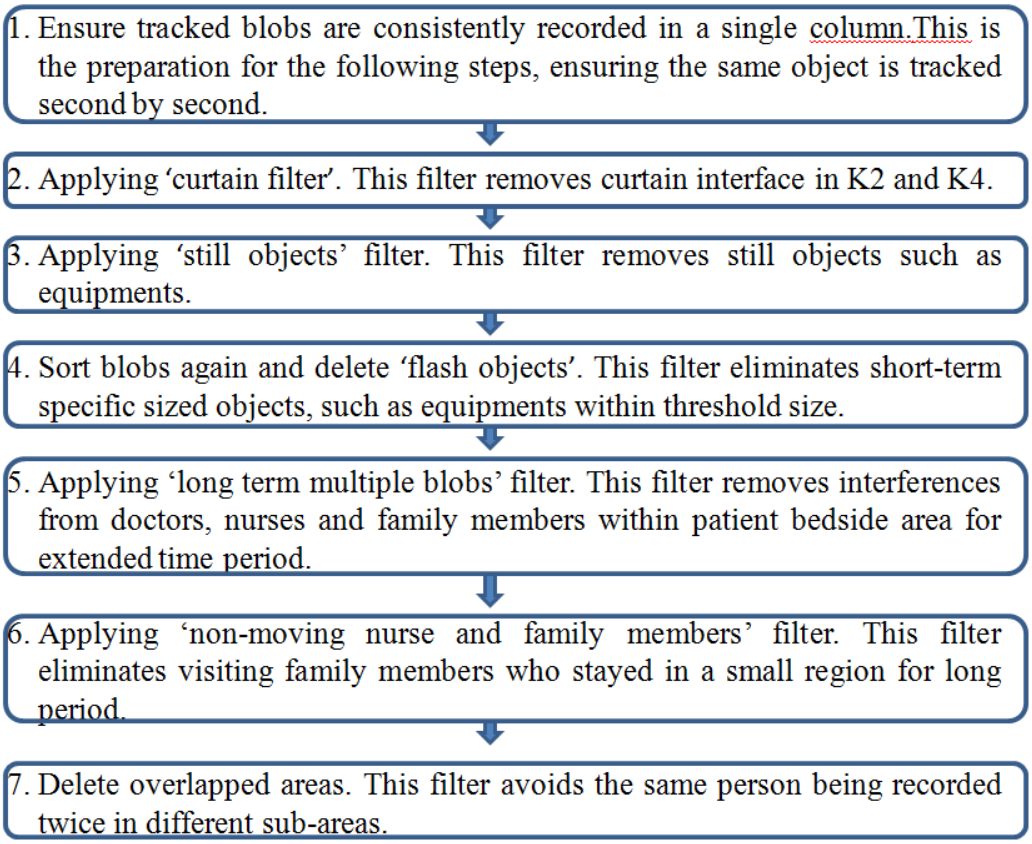


Figure 5.18: Filter flow chart in K2 and K4 sub-area.

5.4 Filter in K1 and K3 area

There are 6 filters applied in the K2 area to remove 'noise' patterns, leaving walking patterns recognized as nursing interventions. The same 6 filters are applied in the K4 area. According to 67 hours RGB video footage comparison, the error after each filter is no more than 3%. The total error after all filters is 4%.

For the K1 and K3 areas, there is no 'curtain' filter as the curtain cannot be detected, no 'long term multiple blobs' filter, as discussion rarely happens in K1 and K3, and no 'overlapped area' filter, as K1 and K3 are distinguished as clinically intensive areas, so any interventions in K1 and K3 are preserved. The procedure to filter interferences in K1 and K3 areas are demonstrated in Figure 5.19.

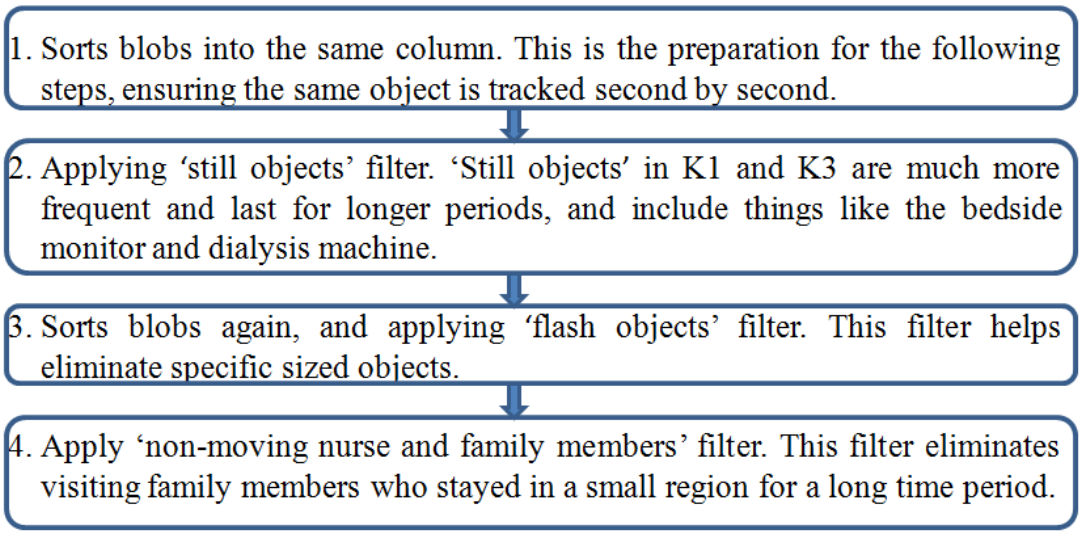


Figure 5.19: Filter flow chart in K1 and K3 sub-area.

Nursing intervention after each filter is compared with RGB video. In K1 and K3 area, the total detection errors are less than 4%. Hence, the system represents to the clinical work environment and can be used for nursing work in the ICU bedside. Overall, these filters are generic in what they do, and only customised to the specific locale. They would be needed in any ICU space, but can be customised differently depending on workspace set up.

Figure 5.20 shows the total nursing intervention in area K1 for a particular 12am~10am period after applying all 3 filters. A total of 4749 seconds (~ 1 hour 19 minutes) of clinical activity was recorded in this region over the10 hours. Figure 5.20 also shows nursing intervention dwell time for any interventions lasting longer than 5 seconds. This removes scenarios where the nurse quickly walks through the detection area. A total of 4335 seconds (~ 1 hour 12 minutes) was recorded, which is 91.3% (4335/4749) of total nursing intervention and 12.0% (4335/36000) of total time. As total nursing intervention time and nursing intervention dwell time similarly explain nursing work, total nursing intervention time is used to quantify workload intensity in upcoming chapters.

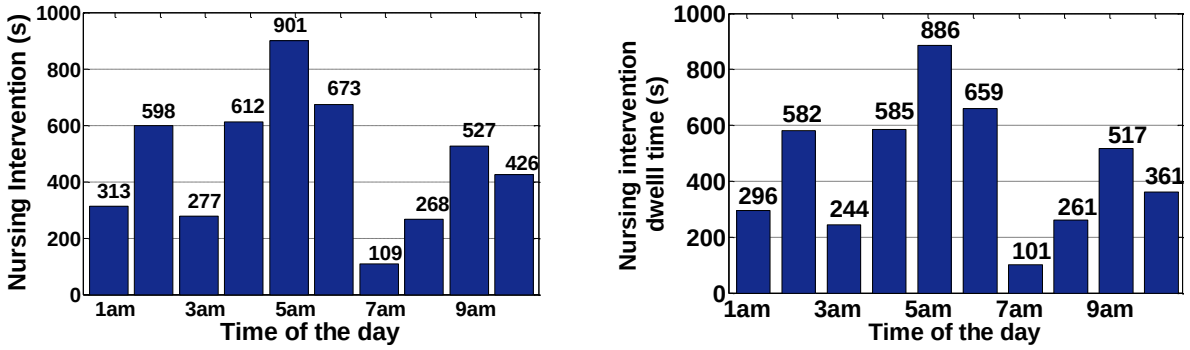


Figure 5.20: Left: Nursing intervention from a given 12am-10am in the area K1. The total intervention time is 4749 seconds. Intervention time in each hour was labelled on top of each bar. Right: Nursing intervention dwell time from 12am-10am in the area K1. The total intervention dwell time is 4335 seconds, which is 91.28% of total nursing intervention.

A probability distribution contour and heat map for these clinical activities in the K1 area are shown in Figure 5.21. In Figure 5.21 (left), the entire region is meshed into 50×50 elements, p(x) is the probability of blob appearance in each of these elements. The cumulative of probability distribution in entire region is 100%. The heat map in Figure 5.21 (right) shows the contour of the probability distribution interpreted as a 'top view' of Figure 5.21 (left). According to Figure 5.21 (right), it shows the highest nursing intervention density was along bedside. Next to the medicine trolley has the second highest intervention density, and the monitor area has the least. These results correspond to the real nursing interventions observed.

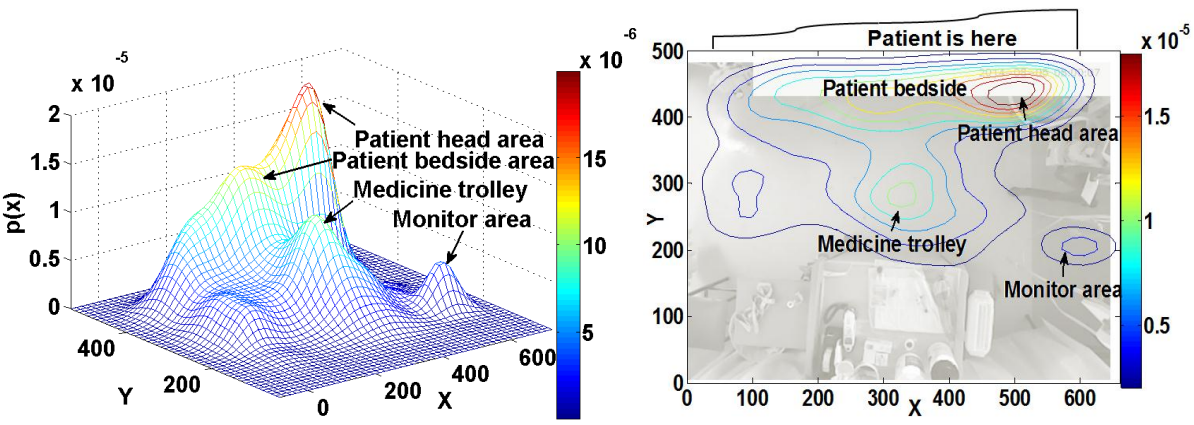


Figure 5.21: Left: Contour of cumulative nursing intervention distribution on a given 12am~10am. Right: Contour of probability density or heat map labelled to show area next to the patient head and other clinical equipment. Units of X and Y are all in pixels.

5.5 Performance of filters in all 4 areas

Table 5.1 shows the nursing intervention distribution and heat map in K1, K2, K3, and K4 areas before and after using all the filters. The same 12am~10am time period is used across K1-K4. It shows nursing intervention time reduced dramatically in all 4 areas when non-nursing activities are filtered. In addition, heat maps in all 4 areas changed significantly after filtering. The results thus show the true, therapeutic nursing activity.

Table 5.1: Nursing intervention and heat map in each area before and after using filters to eliminate 'noise' intervention. Units of heat maps are all in pixels.

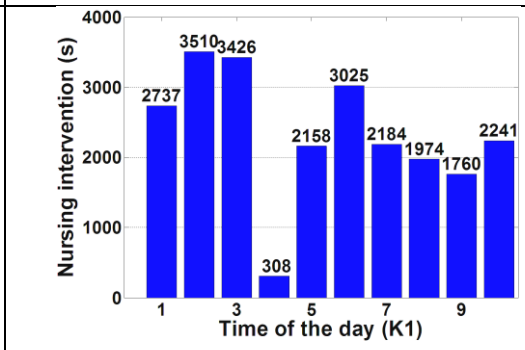
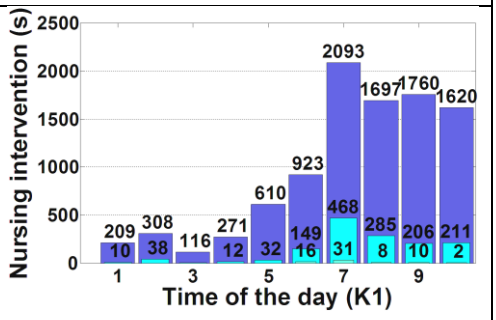
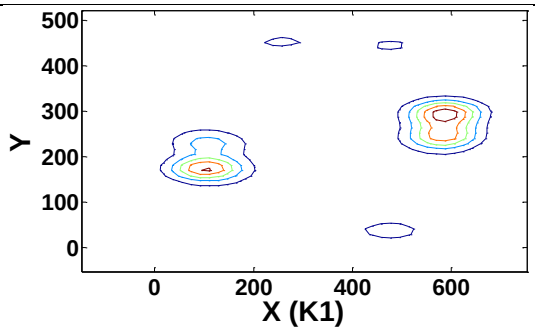
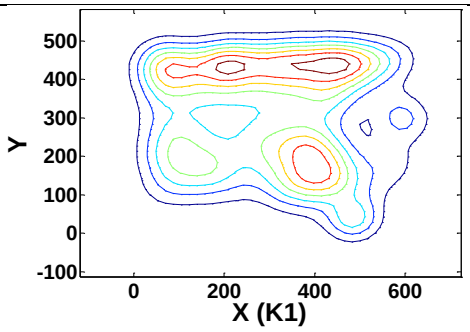
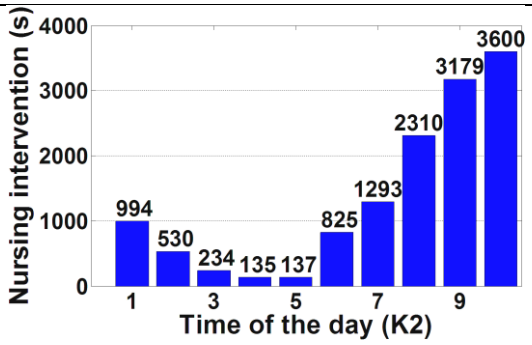
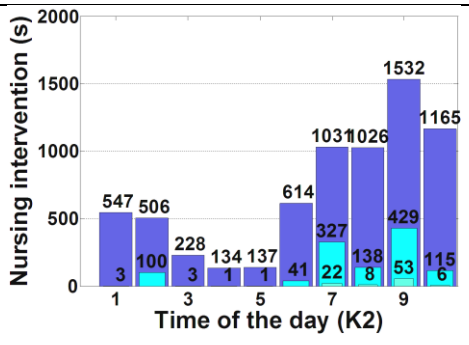
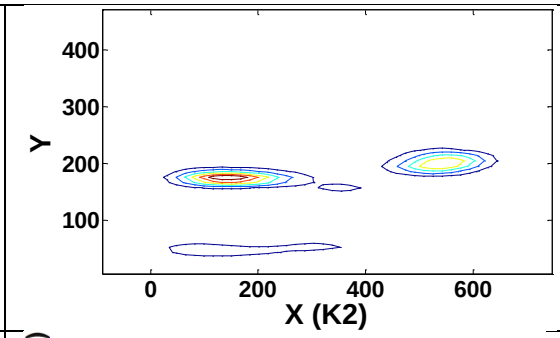
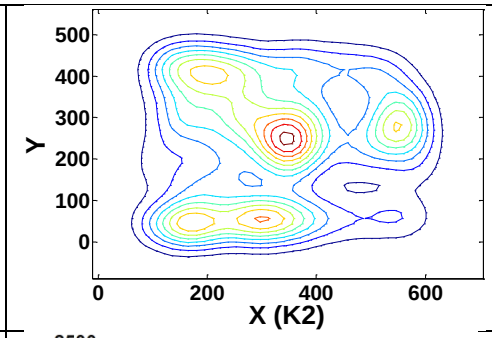
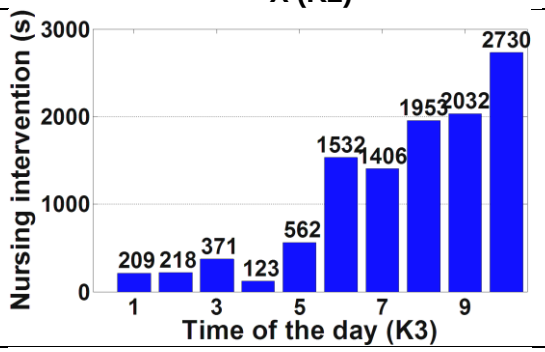
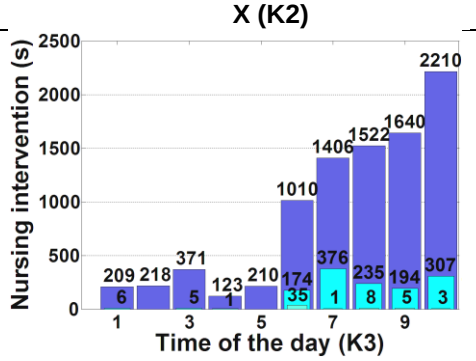
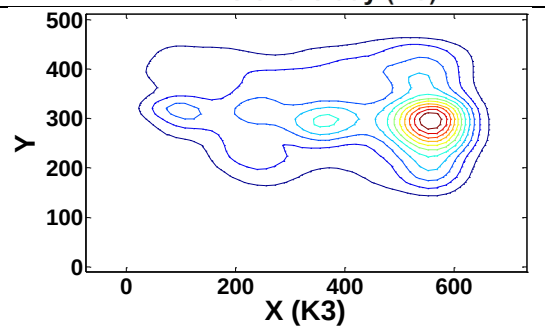
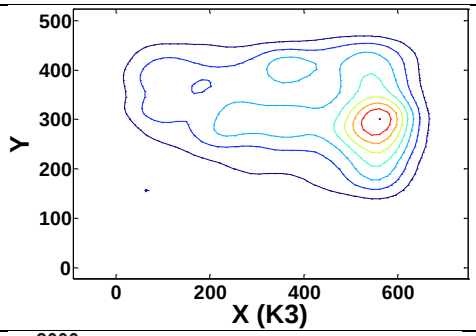
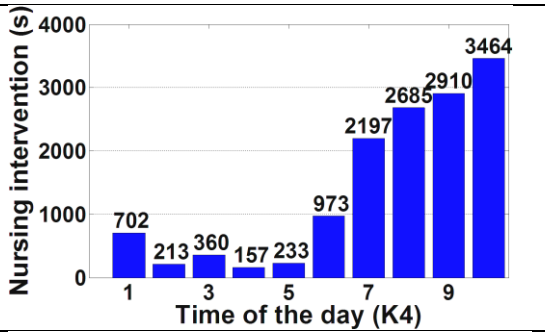
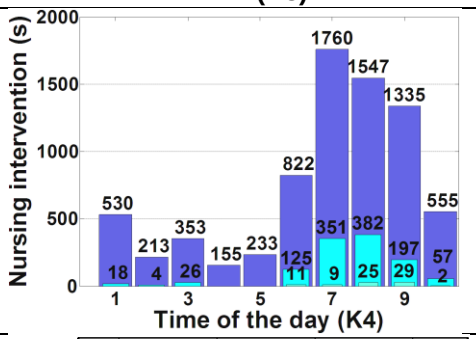
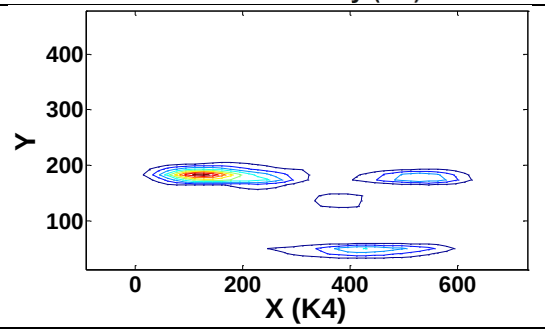
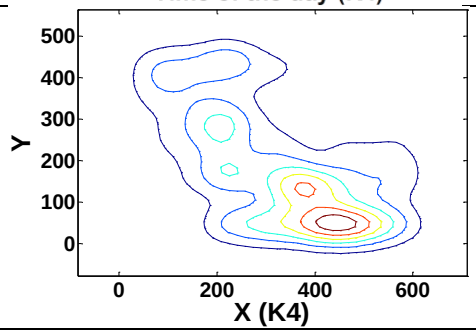
		Before applying filters	After applying filters
K 1	Bar Chart		
	Heat Map		
K 2	Bar Chart		

Table5.1 continued on the next page…

... Table 5.1 continued

	Heat Map		
K 3	Bar Chart		
	Heat Map		
K 4	Bar Chart		
	Heat Map		

5.6 Summary

This chapter presents the implementation, set up, and initial validation of CATS in a Christchurch Hospital ICU bedspace. The system is further customised to filter potential non-nursing noises or interferences that are not directly related to therapeutic nursing interventions. It was found that the system works with a range of 0.09% - 4% error and this error should be clinically acceptable for evaluating effort versus patient illness severity. Given the subjective and variably interpreted nature of current nursing workload forms, the CATS system is expected to give a more accurate description and break down of nursing workload in a more objective and automated fashion.

In the next chapter, the post-processed nursing intervention is further validated by comparing with manual observation and specific separate recording of actual nursing work based on a known nursing effort scale [87]. A correlation between observed nursing intervention and post-processed nursing intervention can be found and this outcome can translate system captured nursing intensity into accepted clinical nursing intensity.

Chapter 6 Clinical Validation and Relative Preliminary Results

6.1 Introduction

Implementation of the clinical activity tracking system (CATS) in an actual clinical environment requires additional fine tuning. Using manually recorded nursing interventions derived from RGB video footage, a series of filtering algorithms were developed in Chapter 5 to capture actual nursing work. However, work can only be monitored and quantified if it occurs within the CATS detection area. Activities such as patient meal preparation, emptying urinal container, washing hands, and the medicine trolley restocking are likely to occur outside of the CATS detection area.

In addition to nursing work that occurs outside of the detection area, changes to the patient bedside layout, such as patient bed not being placed in the centre, may lead to some nursing interventions not being detected. In addition, post-processing may wrongly delete some real nursing interventions. All these scenarios could cause recorded nursing intervention to be different than the actual nursing intervention at the patient bedside. Thus, it is necessary to perform CATS system validation through manual observation of clinical activities.

This chapter presents a detailed CATS system validation that compares CATS detected clinical activities directly to clinical activities recorded through manual observation. The relationship between observed nursing interventions and system recorded interventions is examined, and this relationship can be used to calibrate the system and obtain a real total intervention time. It is also investigated whether a single or double Kinect sensor covering a

strategic detection area gives a good estimate of total nursing intervention. This would reduce cost and simplify system set up and data processing. Heat maps for nursing workload are also generated to monitor the nursing workload and intensity.

6.2 Validation method design

In the Christchurch hospital ICU patient bed unit 7 (as shown in Figure 5.1), the K1 area is where the mechanical ventilator, patient vital sign monitor, and medicine trolley are located. K3 is where the intravenous pumps for medicines, IV pole for fluid, feed pumps, and suction pumps are located. Thus, the K1 and K3 (K1 + K3 ➔ K13) areas contain the most direct nursing activities or nursing workload [2, 78-80]. Comparatively, in K2 and K4 (K2 + K4 ➔ K24), activities such as recording patient 24h charts and laboratory reports, communicating with doctors and families were observed. The K2 and K4 areas are relatively less clinically intensive.

A trained ICU researcher performed manual observations on nursing workload at the bedside. A single researcher performed all observations in this study to eliminate user bias, using the observation chart shown in Appendix 6.1. The researcher calculated the nursing intervention minutes for each observed hour. This observation was conducted one hour per day, and the total nursing intervention within that hour is recorded and compared to CATS recorded nursing intervention. A total of 30 days of data were recorded in February and March, 2015. From this data, 24 out of 30 observation hours were between 8am and 10am, as nursing workload is the most intense at this time of the day, based on observation and published data [2, 216]. A single researcher performs the study to eliminate user bias.

The direct nursing intervention time every hour observed by the researcher is denoted as A_{time}.

For this 30-day period, the hours of CATS recorded nursing intervention time (C_{time}) corresponding to when direct nursing intervention were manually observed (A_{time}), were extracted from CATS. The A_{time} for the 30-day period is compared with C_{time}. The relation between A_{time} and C_{time} in K13 and K1234 (K1 + K2 + K3 + K4 ➔ K1234) (all area) of the CATS is assessed using Pearson's linear correlation [217]. The first order relations were generated for A_{time} versus C_{time} in K13 and K1234. Bland-Altman plots for the agreement of A_{time} and C_{time} in K13 and K1234 are also generated for comparison [218, 219]. It is important to note that A_{time} observations do not account for location. Thus, A_{time} is more comparable to K1234.

Using the relation between A_{time} and C_{time}, the 'actual' time spent on clinical activities around the patient bedside can be calibrated using a correlation factor to the direct observation and quantified. After obtaining the relation between A_{time} and C_{time}, a 60-day period consisting of the first 30-day sections of CATS monitoring were analysed between February and April, 2015. During this 60-day period, a total of 13 patients with different clinical diagnostics were included, based on their use of that bedspace and under ethics approval, and their corresponding bedside nursing activities were investigated.

6.3 Relationship between CATS and actual nursing intervention

Figure 6.1 shows the observed nursing intervention and CATS detected nursing intervention in the 30-hour observation period. The actual observed nursing intervention time is mainly falls between the CATS recorded levels for K13 and K1234.

Figure 6.2 shows the comparison between A_{time} and C_{time} for the 30-hour period. For K13, a strong correlation was found between C_{time} and A_{time}, with R_{K13}= 0.882. As for K1234, a

moderate correlation of R_{K1234}= 0.697 was found. The linear calibration relationship derived from linear regression for the total activity time spent in K13 and K1234 versus the manual observation is shown in Equation 6.1, Equation 6.2 and Figure 6.2.

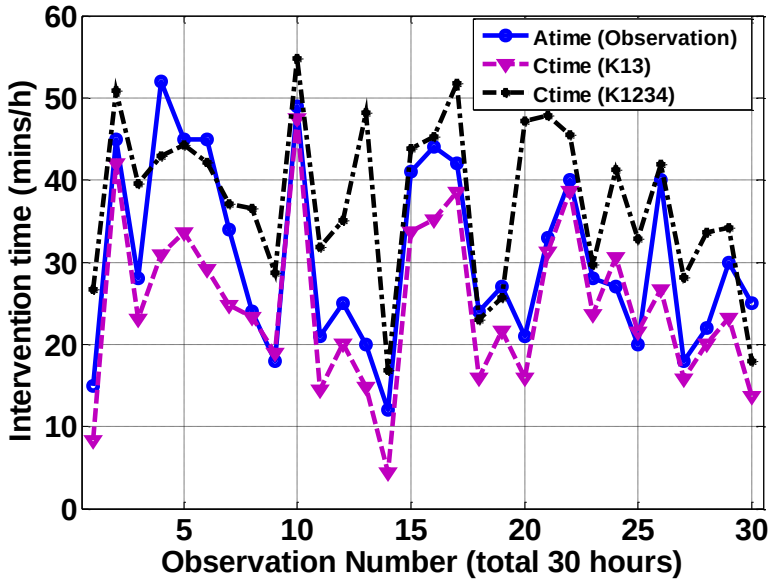


Figure 6.1: 30-hour observed nursing intervention and CATS detected nursing intervention. K1 + K3 is intervention in K13 area, K1 + K2 + K3 + K4 is intervention in K1234 area.

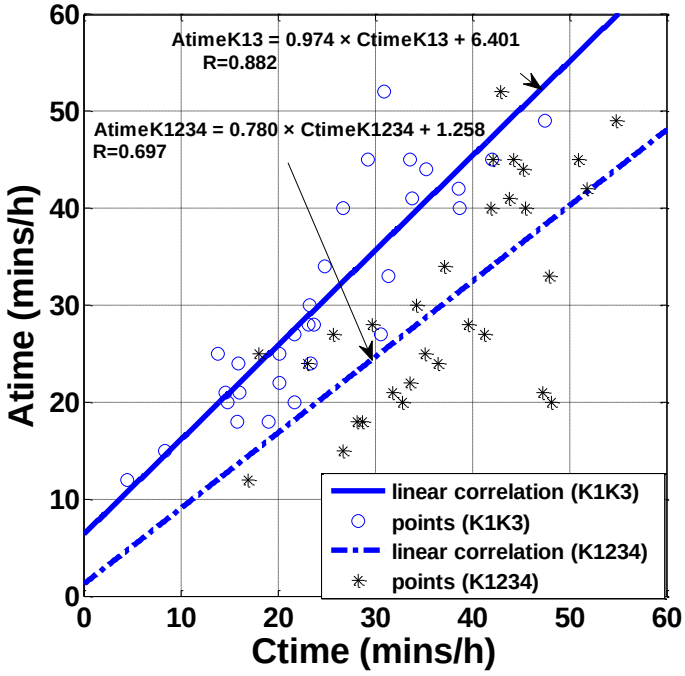


Figure 6.2: Correlation plot of observed intervention (A_{time}) and CATS detected intervention (C_{time}). The X-axis is the CATS monitoring (C_{time} in minutes/hour) and Y-axis is the corresponding observed intervention (A_{time} in minutes/hour). The solid line represents the linear relation between A_{time} and C_{time} calculated in area K13. The dashed line is the relation between A_{time} and C_{time} in K1234.

$$A_{timeK13} = 0.974 \times C_{timeK13} + 6.401 \quad (6.1)$$

$$A_{timeK1234} = 0.780 \times C_{timeK1234} + 1.258 \quad (6.2)$$

A further correlation analysis was performed using only activities that occurred in either K1 or K3 separately, versus manual observation, A_{time}. The results are shown in Figure 6.3. A strong correlation was found between C_{time} and A_{time} in K1, with R_{K1}= 0.739 and a moderate correlation of R_{K3}= 0.565 was found for K3. These results indicate differences are likely due to the necessity and frequency of use of equipment in each area (K1, K3). Specifically, K1 with the mechanical ventilator and medicine trolley is most directly related to patient activity and care, and thus more reflective of total effort in A_{time}.

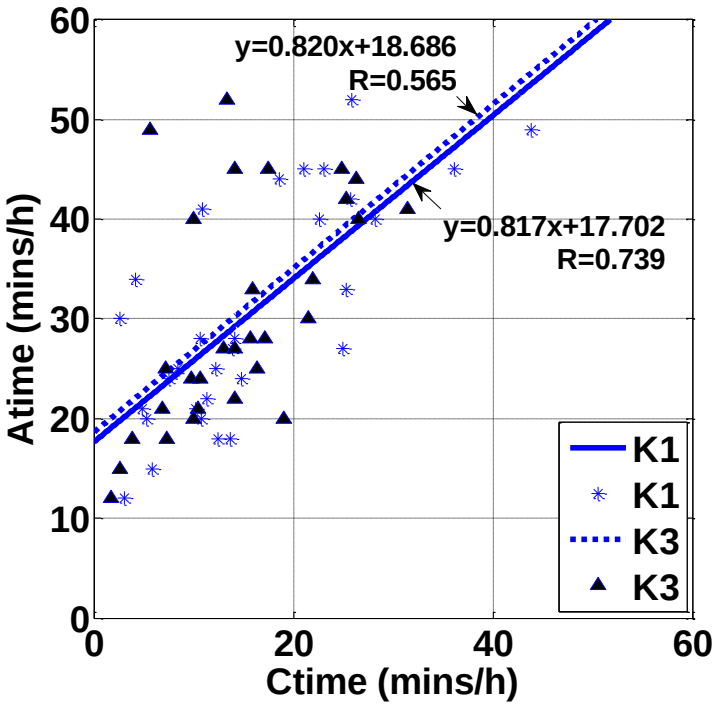


Figure 6.3: Scatter plot of observed intervention time (A_{time}) and CATS detected intervention time (C_{time}).

Results in Figure 6.3 show that neither K1 nor K3 alone captures all the actual intervention time and thus, a sum of nursing intervention in K1 and K3 can provide a better prediction of

actual nursing intervention, as seen in Figure 6.2 and Equation 6.1. Between K13 and K1234, interventions in K13 area have higher correlation with observed nursing intervention (R_{K13}= 0.882). This higher correlation is due to most direct nursing interventions occurring in the K13 area, whereas activities in K24 are more variable and are indirect nursing interventions. Thus, Equation 6.1 can be best used to convert CATS captured time (C_{time}) to actual direct nursing intervention (A_{time}).

Figures 6.4 and 6.5 show the Bland-Altman plot between manual observation (A_{time}) and CATS captured nursing interventions in area K13 ($C_{timeK13}$) and K1234 ($C_{timeK1234}$), respectively. Results show that CATS monitoring in K13 is lower than total time in observation, A_{time}, with a positive bias of median 5 minutes per hour, compared to 6 minutes bias in Equation 6.1. CATS monitored intervention time in K1234 is higher than that actually observed, with a negative bias of median 6 minutes per hour, compared with a positive *y* intercept of 1.2 mins in Equation 6.2. These results match the actual clinical case, where most direct nursing interventions occur in K13 and indirect nursing interventions occur in K24.

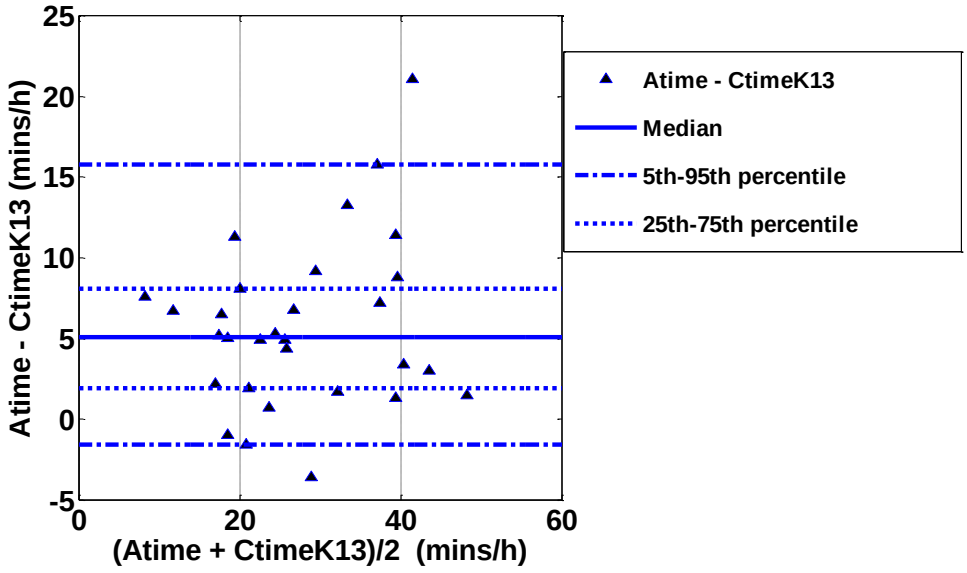


Figure 6.4: Bland-Altman plot showing the agreement between manual observation and CATS monitoring in K13.

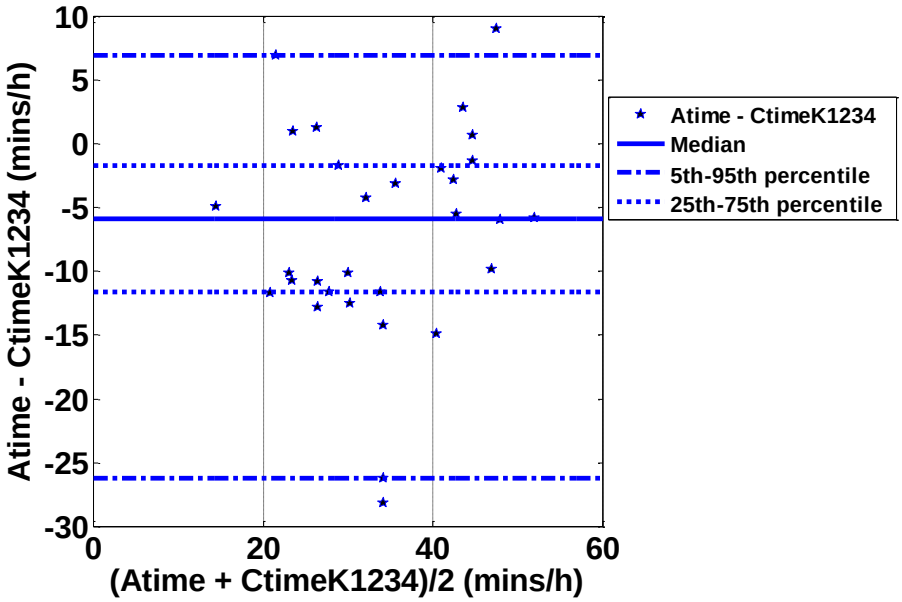


Figure 6.5: Bland-Altman plot showing the agreement between manual observation and CATS monitoring in K1234.

6.4 Day time-night time intervention distribution

Using Equation 6.1, the 30-day and 60-day A_{time} distribution during different hours of the day were calculated, and are shown in Figures 6.6 and 6.7. The corresponding median A_{time} is presented in Tables 6.1 and Table 6.2.

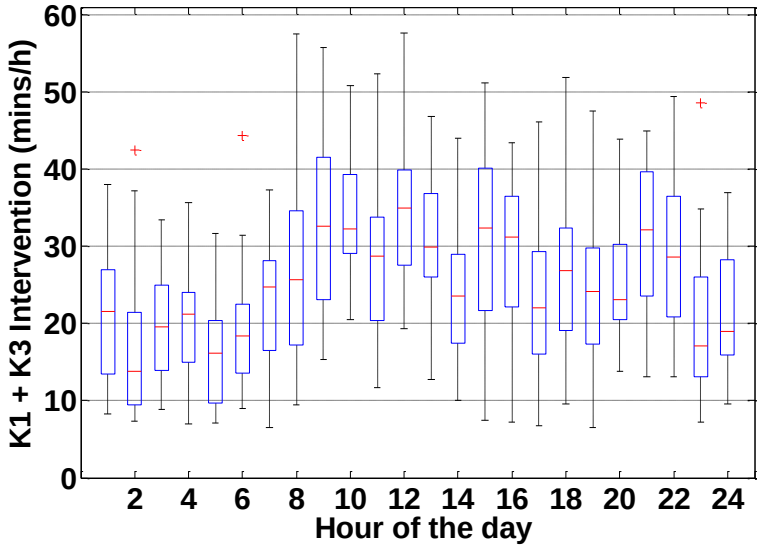


Figure 6.6: 24-hour nursing intervention distribution based on the initial 30 days observational study.

Table 6.1: Median intervention in each hour (30 days of observation)

Hour (1 – 8)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Intervention (min)	21.5	13.8	19.6	21.2	16.1	18.4	24.8	25.7
Hour (9 – 16)	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Intervention (min)	32.6	32.2	28.7	35.0	29.9	23.6	32.4	31.2
Hour (17 – 24)	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Intervention (min)	22.0	26.8	24.2	23.1	32.2	28.6	17.1	18.9

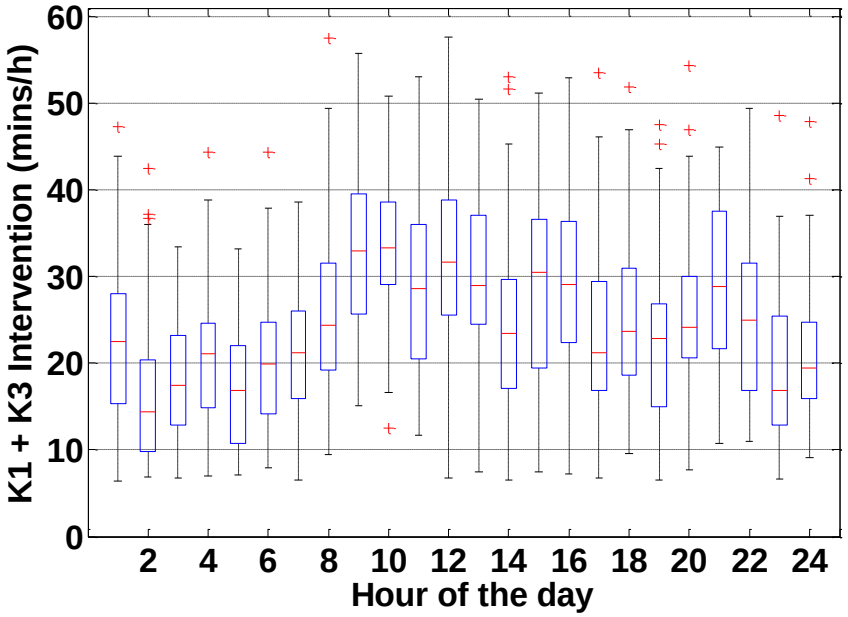


Figure 6.7: 24-hour nursing intervention distribution based on a 60 days of observation.

Table 6.2: Median intervention in each hour (60 days of observation)

Hour (1 – 8)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Intervention (min)	22.5	14.4	17.4	21.1	16.9	19.9	21.2	24.3
Hour (9 – 16)	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Intervention (min)	32.9	33.3	28.6	31.6	28.9	23.5	30.5	29.1
Hour (17 – 24)	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Intervention (min)	21.2	23.6	22.9	24.2	28.8	24.9	16.8	19.5

Figure 6.6 and Table 6.1 show the 24-hour A_{time} distribution for the first 30-day period. The median A_{time} during 2300-0700 hours, overnight, is 19.3 minutes/hour. Comparatively, median A_{time} during 0700-2300 is 28.7 minutes/hour, and was 1.5 times higher than 2300-0700 hour. It was found that the median time during 0700-2300 is higher because more nursing activities happened during the morning and evening shifts, such as meal preparation and dressing patients. In addition, more people visit the patient at these times. For example, doctors do routine checks in the morning, X-ray and ultra-sound scans typically happen during day time, and family often visit the patient during day or evening. In contrast, the night shift only contains the basic routine checks, such as temperature or sedative level check.

Similar trends were also observed in the A_{time} distribution for the 60-day period, as shown in Figure 6.7 and Table 6.2, where median A_{time} during 0700-2300 was 26.8 minutes/hour, which was 1.4 times higher than 19.7 minutes/hour at 2300-0700. The median and distribution of time spent in nursing activity during the first 30 days by 24-hour period, and the subsequent 30 days was not statistically significantly different ($p = 0.327$ using Wilcoxon ranksum test and $p = 0.622$ using two sample Kolmogorov-Smirnov test). Thus, the distributions were consistent over the entire 60-day period.

6.5 Heat maps

Figure 6.8 shows the heat map on a particular patient day. Figures 6.8 (a-d) show the corresponding heat maps in K1-K4. Each area is divided into a 16×12 elements sub-area, with 40×40 pixels per sub-area, approximately $0.1 \times 0.1 m^2$. When any object entered any sub-area, total nursing intervention in that sub-area starts to accumulate. The maximum value is set as 900 seconds (15 minutes/ day). Any sub-area with more than 15 minutes is converted to the darkest color. Figure 6.8 (e) shows the combination of all 4 areas to form an entire

bedside intervention heat map. It shows clearly that the patient bedside, especially the two head sides (K1 and K3), and the medicine trolley have the highest intervention intensities in the K13 region. In the K24 area, the interventions are concentrated at the chart table, where most supporting activities happened.

6.6 Discussion

In this study, high (R_{K13}=0.882) and good (R_{K1234}=0.697) correlations were found between A_{time} and C_{time} in K13 and K1234 area. This result shows that CATS was able to estimate the actual bedside clinical activity based on time and location of each activity being recorded. As shown in Figures 6.4 and 6.5, the $C_{timeK13}$ tends to be lower than A_{time}, with approximately additional 5 minute bias. This bias is due to nursing activities that occur out of the K13 area. Comparatively, $C_{timeK1234}$ tends to be higher than A_{time}, because it may include additional supporting works in area K1234, such as data recording, communicating, un-filtered family member consulting as well as activities not considered as clinical activity. The difference between A_{time} and C_{time} is due to the fact that only direct nursing activities is included in A_{time} (Category 1, Appendix 6.1), whereas other nursing activities (Category 2-9, Appendix 6.1) inside the badspace are captured by C_{time}.

It was found that direct interventions occur primarily in the K13 area, while indirect interventions can occur in any of K1, K2, K3, and K4 or even out of the detection area. In this study, direct nursing activities are of particular research interest, as they represent the major nursing workloads that are directly related to patient's recovery. Thus, Equation 6.1 for calculating A_{time} in K13 is used instead of Equation 6.2 to estimate actual A_{time} in K1234 as it is more targeted to the application of this study.

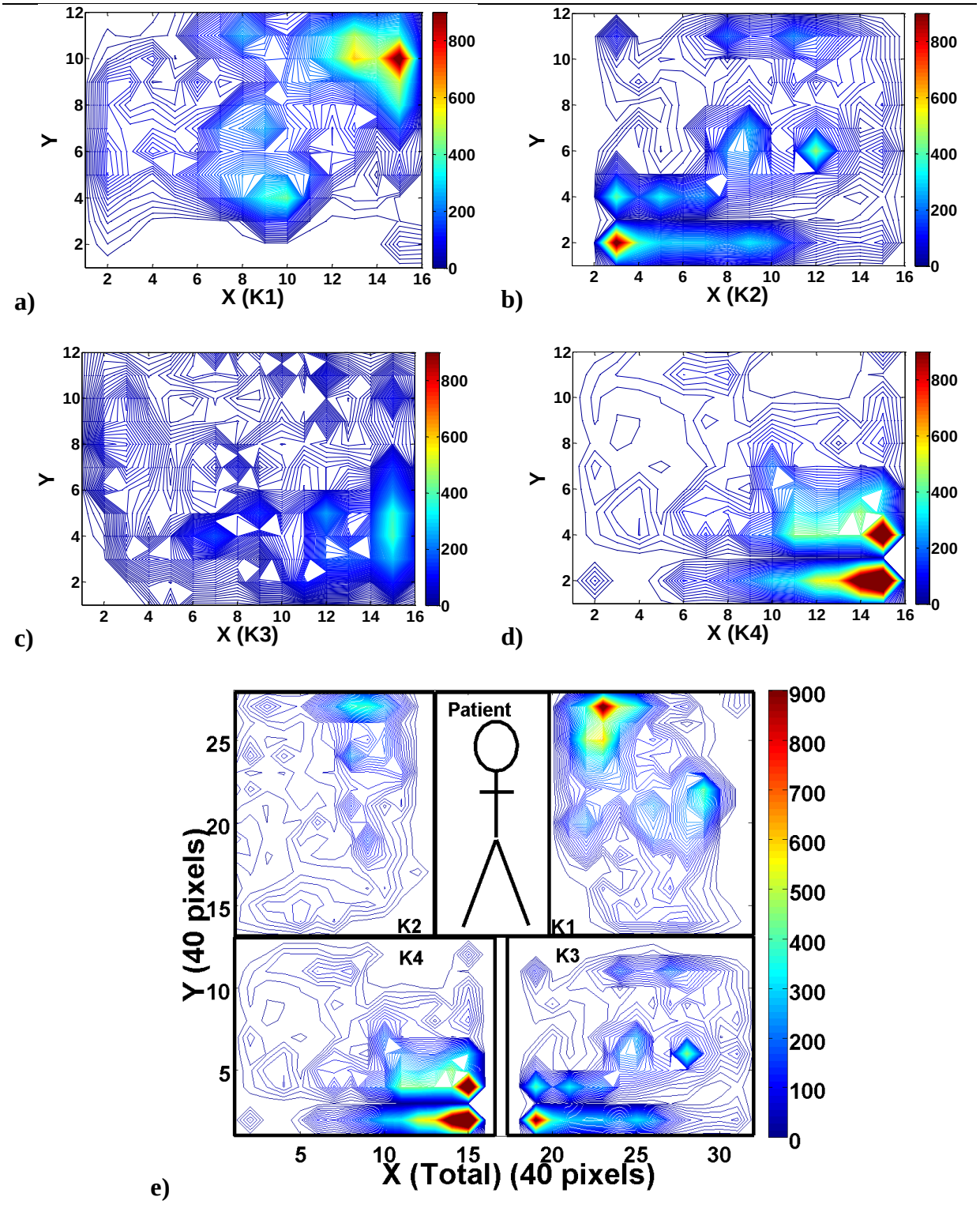


Figure 6.8: Heat map on a particular patient day. (a-d) show each sub-area nursing intervention in K1~K4 respectively, and (e) shows the combination of 4 areas.

From the 30-day and 60-day 24-hour A_{time} distributions, it was found that the workload during 0700-2300 is 1.4-1.5 times higher than 2300-0700. This observation suggests that the total amount of time spent on direct intervention during night time is generally lower, as less specialized or intensive clinical activities are likely to be carried out. However, the lower A_{time} does not imply that overall workload during this period is lower. In particular, during night time, there could be comparatively less clinical staff and other resource support. Thus, the workload may be more equivalent than time alone can suggest.

Heat maps showing nursing intervention intensity in each sub-area could be generated hourly, 6 hourly, 12 hourly, or daily. Combinations of heat maps and bar charts yield a better understanding of specific nursing demands. Workload in a sub-area can be translated with this data to requirements of specific equipment. For example, respiratory failure and renal failure patients can have higher nursing intervention near the mechanical ventilator at any hour.

Limitations:

One of the limitations of this system is that it requires Equations 6.1 and 6.2 to estimate the actual time spent on every nursing intervention. For Equation 6.1, while there is almost a 1:1 relation, an offset of 6.4 minutes between A_{time} and C_{time} was obtained. Thus, there may be instances where non-plausible A_{time} is estimated. For example, using Equation 6.1, if the C_{time} is 55 minutes or more, the estimated Atime becomes more than 60 minutes per hour. However, this issue can be overcome by setting the limit to 60minutes/ hour during post processing, and such a large C_{time} was not close to being observed.

Data was collected over 30 and 60 days and analyzed. Based on this data, only a generalized trend can be inferred. In addition, 13 patients with different diagnostics were included in this study, and the preliminary CATS results were not able to provide information on patient-specific disease state and their corresponding clinical activities. Thus, additional CATS data in conjunction with the patient's clinical diagnostic monitoring are required to set up the patient-specific workload distribution across patient disease/diagnostic.

6.7 Summary

This chapter presents the validation of a novel approach to quantify the time spent on every detected direct nursing intervention in ICU. The system is able to automatically record and estimate nursing intervention. In the preliminary analysis using a distribution based on 60 days of nursing intervention, it was found that patients receive higher nursing care at specific times, and there are significant differences in the overall workload distributions. These results can potentially be used as a guide to optimize and manage nursing resources to reduce nurse workload and provide balanced care to each individual patient.

In the next chapter, different existing standard patient clinical score systems are presented. Each system is reviewed, and several are applied in this study. By using different score systems, measuring and comparing patient sickness and nursing effort is possible. Specifically, these patient clinical scores can be used as comparator to CATS measured nursing intervention to provide unique insight to the clinical workload that was not available before.

Chapter 7 Comparison of different clinical scoring systems and relative results

7.1 Introduction

Quantifying nursing workload is a challenging task as workload is affected by many potential patient factors including: age, acuity level, sedation level, and diagnosis. There are also many unpredictable factors, such as sudden changes of patient condition that further complicate a multi-task and multi-factorial job, with many diverse tasks.

In the last decades, several assessment tools were developed to evaluate nursing workload. The therapeutic intervention scoring system (TISS) created in 1974 [81], was designed to evaluate patient severity based on 57 possible clinical therapeutic interventions. The updated TISS-76 in 1983 [82] contains 76 therapeutic interventions, each of which is given a workload score out of 4. An appropriate workload for a single nurse is assumed to total 40-50 points.

Another assessment tool comes out of the project research of nursing (PRN) framework, which was conducted during 1980-1987 [83]. The PRN lists 214 indicators or tasks that nurses complete on behalf of patients during a 24-h period. Each indicator or task is assigned a point value that represents the time to complete a specific nursing intervention, as well as the number of times the task will be completed on a shift. However, obtaining PRN results is extremely time consuming, and thus unsuitable for routine use.

The OMEGA study in 1986 [83] described 86 therapeutic interventions grouped into 3

categories. These were measured at the end of patient ICU stay, and the data was analysed as a whole to give an assessment of global workload and use of resources. Thus, the result is an average workload value over a patient's ICU stay.

The time oriented score system (TOSS) [79] was developed in 1991. This score represents a direct temporal evaluation of nursing workload. The score is expressed in minutes, collected as survey sheet from on-shift nurses. Results are reliable and relatively simple, but data collection requires experienced nurse assistance and can be subjective.

The EURICU-1 study in 1996 [85], aimed to categorize patient into 4 groups, and each patient category was assigned a correlated nurse-to-patient ratio. However, this category scoring system has been criticized for not accurately reflecting the actual nursing time spent in each patient category. Further, it was also criticized because it categorizes patient need rather than indicating nursing workload as a direct result of patient dependancy [220, 221].

More recently, the TISS framework was further updated, and TISS-76 was updated in 1996 to TISS-28 [2], representing a simplified version of TISS-76, containing only 28 therapeutic interventions. Each of the TISS-28 point is calibrated to represent 10.6 minutes of work in each 8-hour shift. Thus, a nurse can deliver work equal to a total 46 points per 8-hour shift (480 minutes maximum).

Nine Equivalents of Nursing Manpower (NEMS) [86] further simplified the TISS-28 to 9 equivalent therapeutic interventions. Each nurse can deliver 45-50 points per day. Both TISS-28 and NEMS are patient oriented systems, evaluating nursing workload based on potential patient demand as a function of relative severity level.

The Nursing Activity Score (NAS) [78] was established in 2003 and is derived from TISS-28. It adds 5 more new nurse oriented items, aiming to describe nursing activities that are not necessarily correlated to severity of illness. It was able to explain 81% of nursing time, while TISS-28 only explains 46% of nursing time [78]. However, these 5 new added items are not accessible from a patient's daily 24-hour chart, and thus it requires subjective nurse survey feedback during each shift to obtain an up to date score.

Besides nursing workload assessment systems, patient severity scoring systems, such as APACHE (Acute Physiology and Chronic Health Evaluation) [222], APACHE-II, APACHE-III [210, 223], SOFA (Sequential Organ Failure Assessment) [212], and SAPS-II (Simplified Acute Physiology Score) [224], are used as tools to estimate required nursing resources. These systems are easily accessible because every item for these scores is recorded in a patient's daily 24-hour chart or physiology report. Thus, they are more likely to be calculated during their length of stay (LOS), and more accessible. Their limitation is that their use assumes severity and workload are strongly correlated, which may not be strictly true in practice.

Many researchers in the last decade have pointed out that severity of illness may be an appropriate component of at least a measure of nursing intensity [225-229]. However, these patient severity assessment systems are patient-oriented and thus unlikely to describe nursing workload perfectly. In particular, patients with equal severity scores may require very different levels of nursing interventions and effort.

A study by Adomat et al. [87] used a video camera to record nursing activity in the ICU and

concluded that the existing nurse-to-patient ratio classification is inappropriate. It found that nurses may spend less time with more critically ill patients. For example, fully sedated mechanically ventilated patients do not necessarily receive more nursing input than patients allocated a lower level of dependence and who are thus more awake. These patients are considered more critically ill by every illness severity metric, but researchers have shown there is only a weak or no correlation between patient severity score and nursing workload [230-232]. Thus, there is a clear contradiction in the existing evaluation systems and approaches used to optimise patient-nurse ratio based on severity scores.

As discussed, all patient severity scores, including TISS and NEMS are patient-oriented. While they are more clinically accessible and measurable, they are less likely to transfer well or correlate to nursing workload. In contrast, nurse-oriented workload assessment tools are more likely to describe real nursing demands, but are more subjective and typically require experienced nurses to fill out a checklist during each shift, which adds workload. Finally, there is no standard method to consistently quantify patient and bedside nurse interaction. In short, all patients are different and have different needs, even if they are broadly scored as similar by a severity or other scoring system. It is very unlikely that a 'one size of care' will fit all patients.

This chapter introduces different nursing workload and patient acuity assessment tools. Specifically, it describes the data collecting procedure in detail for calculating TISS-28, NEMS, APS, APACHE-III, SAPS-II, APACHE-II, and SOFA. Patient data collected during the CATS study was used for the analysis performed in this chapter. The distributions of different assessment results are presented. The relationship between TISS-28 and patient acuity scores included in this study was generated, and it was used to predict the nursing

minutes for different assessment tools.

7.2 Literature review

7.2.1 Patient illness severity assessment systems

Acute physiology and chronic health evaluation (APACHE)

Acute physiology and chronic health evaluation (APACHE) was first developed in 1981 [208]. It is a physiologically based classification system for measuring severity of illness in groups of critically ill patients. APACHE-II in 1985 [233] used a point score based upon initial values of 12 routine physiologic measurements, age, and previous health status to provide a general measure of severity of disease, ranging from 0 to 67 points. APACHE-II also provided an approach to compute predicted mortality rates for groups of acutely ill patients[234]. The predicted death rate R is :

$$Ln(R/l\text{-}R) = -3.517 + (APACHE\text{-}II \times 0.146) + (Diagnostic\ Category\ Weight) + (0.603,\ only\ if\ post\text{-}emergency\ surgery) \quad (7.1)$$

where the Diagnostic Category Weight can be found in [233] or [235].

In 1991, APACHE-III was further developed to predict hospital mortality [236] with greater accuracy. It comprised the sum of three components: an acute physiology score (APS), age score, and a chronic health problems score. The score ranges from 0 to 299 (physiology, 0 to 252; chronic health, 0 to 23; age, 0 to 24), as shown in Appendix 7.1 or [237]. In 2006, APACHE-IV was created and validated [238], showing the prediction of hospital mortality with better discrimination and calibration.

In this study, APACHE-II and APACHE-III are calculated for all 23 patients. APACHE-IV

was not analysed as no reliable calculator was found, and the score itself is equal to that of APACHE-III. The difference between APACHE-III and APACHE-IV is the mortality prediction capability. The APACHE-II score and estimated mortality rate were calculated using an online calculator [239]. The APACHE-III is calculated manually by researcher each day. ASP scores, chronic scores, and age scores are calculated along with APACHE-III. The most commonly used unit conversion is presented in Appendix 7.2.

The simplified acute physiology score (SAPS)

The simplified acute physiology score (SAPS) is a severity score and mortality estimation tool developed from a large sample of medical and surgical patients. It was first developed in 1984, using only 14 easily measured biologic and clinical variables to reflect the risk of death in ICU patients [211]. In 1993, SAPS-II was further updated [224] to include an additional 17 variables, comprising physiology, age, type of admission, and 3 underlying disease variables. The result was a score ranging from 0 to 163 points. The SAPS-II score was able to provide an estimate of risk of death without having to specify a primary diagnosis. Hospital mortality can be calculated:

$$logit = -7.7631 + 0.0737(SAPS\text{-}II\ Score) + 0.9971[\ln(SAPS\text{-}II\ Score + 1)] \quad (7.2)$$

$$Mortality = e^{logit} / 1 + e^{logit} \quad (7.3)$$

In 2005, the SAPS III score was developed and validated [240-242]. Customised equations for major areas of the world were computed to assess severity of illness and predict vital status of hospital discharge.

In this study, SAPS-II is calculated for each day of patient stay. Appendix 7.3 shows where to locate the SAPS-II components in the Christchurch Hospital data records. A validated online

calculator [243] is used to calculate SAPS-II and relative death rate. SAPS-III was not analysed as it is not widely used.

Sequential organ failure assessment (SOFA)

The sequential organ failure assessment (SOFA) is a morbidity severity score and mortality estimation tool developed from a large sample of ICU patients throughout the world [244-247]. Unlike other scoring systems, such as SAPS II and APACHE II, SOFA was designed to focus on organ dysfunction and morbidity as a leading cause of ICU death. It thus has less of an emphasis on mortality prediction. SOFA was designed with emphasis on bedside applicability and simplicity using widely available clinical variables.

The SOFA score is made of 6 variables representing 6 major organ systems: respiration, coagulation, liver, cardiovascular, central nervous system, and renal [244]. Each organ system is assigned a point value from 0 (normal) to 4 (high degree of dysfunction/failure), and the SOFA score is the summation of these values across all organ systems. SOFA score is calculated on a daily basis based on the worst physiological measurements of each 24 hours. The SOFA score ranges from 0 to 24, and can also be used to predict ICU mortality, as shown in Table 7.1.

Table 7.1: Correlation between SOFA scores and hospital mortality [212, 247]:

SOFA Score	0-6	7-9	10-12	13-14	15	15-24
Mortality	<10%	15-20%	40-50%	50-60%	>80%	>90%

In this study, SOFA scores are calculated on each day of stay. Appendix 7.3 shows where to locate each item in the Christchurch Hospital. A validated online calculator [248] is used to

calculate SOFA scores and relative death rate for each patient and day of stay.

7.2.2 Nursing workload assessment systems

Therapeutic intervention scoring system (TISS) and nine equivalents of nursing manpower (NEMS)

The therapeutic intervention scoring system (TISS) was published in 1974 by Cullen et al. [81]. This scoring system contains 57 items, each scored 1-4. The sums of scores were used to: 1) determine appropriate utilization of ICU facilities; 2) provide information on nurse-to-patient ratios; 3) validate a clinical classification of critically ill patients into four categories; and 4) analyze the cost of ICU [81]. TISS was updated to TISS-76 in 1983 [82] by Keene et al., extending TISS to 76 items, with each interventions scored from 1-4 points. It assumed that a single nurse can manage a total workload of 40-50 points per day. However, there are four major reasons that TISS-76 is not widely used: 1) It is time consuming; 2) The use of TISS-76 is cumbersome; 3) The items listed do not always adequately reflect patient care activities; 4) TISS-76 does not reflect several other daily activities of nursing staff that are equally important to professionals [2].

TISS-28 [2] was updated in 1996 by Miranda et al. to represent a simplified TISS-76, containing 28 therapeutic interventions, with each item scored from 1 to 8 points. It stated that a nurse can deliver work equal to 46 points per 8-hour shift, which translate each TISS-28 point to 10.6 minutes of each 8-hour shift. Its reliability has been validated [2, 102, 249, 250]. Because of its simplicity, TISS-28 has been widely used in different scenarios [101, 251-254] and it can be calculated based on computerized data [255].

The nine equivalents of nursing manpower (NEMS) score was developed by Miranda et al. in 1997 [86]. It further narrows down the TISS-28 into 9 nursing interventions, with each

intervention score ranging from 3 to 12 points (66 point in total). The total NEMS score is used to measure ICU nursing workload. In 2004, an automatic system was developed [256], using a patient data management system (PDMS) to automatically calculate NEMS [257, 258]. The accuracy of NEMS has been validated in some studies [259-261].

In this study, items required to calculate TISS-28 and NEMS scores are collected for every patient and day of stay. TISS-28 and NEMS scores are manually calculated each day. Appendix 7.4 shows the detailed calculation and items required.

Nursing activity score (NAS)

The nursing activity score was created in 2003 by Miranda et al. [78], aiming to determine the nursing activities that best describe nursing workload and attribute weights to these activities. This score system is derived from TISS-28, adding 5 new items and 14 sub-items describing nursing activities. It has been shown NAS explains 81% of the nursing time, while TISS-28 only explains 43% of nursing time [78]. Performance of the NAS has been validated in other studies [102, 262, 263].

Even though NAS is a nurse-orientated tool that could better explain nursing workload compared to patient-oriented tools, such as TISS-28, its application remains limited. In particular, there are 2 main reasons that prevents the NAS from being more widely used: 1) NAS requires extra nursing time to fill out questionnaires [264]; and 2) There is a significant correlation between TISS-28 and NAS [265]. Thus, for well-trained researchers, it is much easier to calculate TISS-28.

Time oriented score system (TOSS)

TOSS was developed in 1991 by the Italian Multicenter Group of ICU Research (GIRTI) [79]. The aim of TOSS was to define an easy and repeatable system for evaluation of nursing workload for ICU patients. During the first 24 hours of ICU stay, the nursing time needed by the patient is collected, which nurses or researcher need to file on a data collection sheet. Each clinical intervention is assigned a relative number of minutes to perform. The number of times it is performed multiplied by the relative intervention minutes yields total minutes needed for each activity. TOSS's major benefit is that it is a direct time evaluation of nursing workload, not mediated by scores related to therapeutic interventions, such as TISS and NAS, or by subjective estimates. TOSS has shown a strong correlation to both SAPS and TISS [79]. However, there remains limited research and application of TOSS, and it is not widely used in the ICU to evaluate nursing workload.

Other scores

Other workload assessment tools include: 1) Belgian Nursing Minimum Data Set (B-NMDS) [266]; 2) Oulu Patient Classification (OPC) [216, 267, 268]; 3) OMEGA; 4) Project Research of Nursing (PRN) [83]; and 5) NASA-TLX [73]. However, there are relatively few studies on these systems, and very little research uses these assessment tools to evaluate nursing workload. Because of their low popularity, they are not considered in this study.

7.3 Data collection and patient selection

In the Christchurch Hospital ICU, the nurse-to-patient ratio is approximately 1:1. During each nursing shift, nurses have to fill out the 24-hour patient chart each hour, an example of which is shown in Appendix 7.5. Patient blood gases are collected every 6 hours if patient has either a central venous line (CVL), arterial line, or peripherally inserted central catheter (PICC) line.

Blood gas analysis is performed using a Radiometer ABL 90 Series machine [269], giving diagnosis results such as pO2, pCO2, pH, and pHCO3. In addition, a blood sample is collected for laboratory analysis in every 24 hours in the morning, or as necessary during the day, if the patient has either an arterial line or PICC line. Laboratory analysis of blood sample generates a blood count and biochemistry report. The blood count report contains diagnostic results such as white blood count (WBC), hematocrit (Hct), and platelets. Biochemistry reports contain diagnostic results, such as sodium (Na), potassium (K), glucose, blood urea nitrogen (BUN), creatinine, albumin, and bilirubin.

All information required to calculate TISS-28, NEMS, APACHE-II, APACHE-III, SAPS-II and SOFA are summarized in Appendix 7.3. The definition of these necessary physiological measurements, their absolute range, reasonable range, and where to locate them in data records are also summarized in Appendix 7.3. Common unit conversions are presented in Appendix 7.2.

This research considered all patients admitted and allocated to 'Bed 7' from August, 2014 to May, 2015. Patients under 18 years of age or patients staying less than 24 hours were excluded. If a patient does not have an arterial line or PICC line, a blood gas sample may not be taken on every patient day. If a patient missed more than 1/3 blood gas reports over his/her LOS, this patient is excluded. In total, 23 patients were included, with a total of 104 patient days. Their LOS in 'Bed 7' varied from 1 to 19 days. Table 7.2 shows the basic demographics for these 23 patients.

Table 7.**2:** Patient demographics

Patient No.	Age	Gender	LOS	LOS in Bed 7	Type of Admission	Diagnosis Code	Comorbidities
1	22	F	2	1	3	1403.01 Internal bleeding	0
2	41	M	5	4	2	601.06 Head/multiple trauma	0
3	22	M	2	1	2	601.08 Head/spine trauma	0
4	72	F	70	10	3	1408.05 Gastrostomy	0
5	54	F	2	2	2	102.01 VF arrest	0
6	77	M	2	1	2	108.01 Hypertension	0
7	55	F	3	3	2	203.01 Aspiration failure	0
8	83	F	2	2	1	1705.03 Anuria post laparotomy	4
9	76	M	12	12	2	201.01 Respiratory Failure + Sepsis	0
10	76	M	7	5	2	502.01 Urinary Sepsis	0
11	65	M	23	6	2	602.11 Chest /thorax trauma	0
12	30	M	14	5	3	1301.01 Infection / abscess surgery	0
13	74	F	1	1	2	212.01 Bacterial Pneumonia	0
14	18	M	1	1	2	604.06 Spinal/multiple trauma	0
15	52	M	1	1	2	407.01 Seizures (Neuromu)	0
16	76	F	2	1	2	110.01 Cardiomyopathy	0
17	21	M	3	3	2	212.01 Pneumonia, bacterial	0
18	73	F	4	4	2	601.03 Head/chest trauma	0
19	60	M	3	2	2	601.04 Head/extremity trauma	0
20	38	F	13	8	2	212.01 Pneumonia, bacterial	0
21	21	F	4	2	2	405.01 Neoplasm neurologic	0
22	48	M	30	10	2	603.01 Burns	0
23	68	M	29	19	2	503.01 Sepsis with shock, not urinary	0

LOS: Days patient admission in ICU. Patient may not stay in bed 7 during entire LOS
Type of Admission: 1) Scheduled (elective) surgical; 2) Medical; 3) Unscheduled (Emergency) surgical.
Comorbidities: 0=None; 1=AIDS; 2=Hepatic Failure; 3=Lymphoma; 4=Metastatic Cancer; 5=Leukemia/Multiple Myeloma; 6=Immune Compromised; 7=Cirrhosis.
Diagnosis code number: followed ANZICS (Australian and New Zealand Intensive Care Society) Data collection Form [270], which is employed by Christchurch hospital diagnosis patients.

During each patient stay, clinical information is collected in the morning, around 5 am – 8 am. TISS-28, NEMS, APACHE-II, APACHE-III, SAPS-II and SOFA scores are then calculated. If any clinical information is missed during these 3 hours, the nearest hour is used to represent patient physiological status. If the nearest hour is more than 24 hours, the missed item is averaged according to the nearest days. Table 7.3 demonstrates clinical items that are calculated each patient day, as well as their definition and score ranges.

Table 7.**3:** Patient clinical evaluation items calculated each day of stay

Items	Defination	Range
TISS-28	Therapeutic Interention Score System-28	0-78
TISS-76	Therapeutic Interention Score System-76: TISS-28=3.33+0.97 × TISS-76	0-200
Time of nursing care	Minutes=TISS-28 × 10.6 /8h	
NEMS	Nine Equivalents of Nursing Manpower	0-66
APS	Acute Physiology Score	0-252
APACHE-III	Acute Physiology and Chronic Health Evaluation-3	0-299
SAPS-II	Simplified Acute Physiology Score	0-163
SAPS-II Estimated Mortality	logit=−7.7631+0.0737(SAPS-II Score) + 0.9971[ln(SAPS-II Score + 1)] Mortality=elogit/1+elogit	0-100
APACHE-II	Acute Physiology and Chronic Health Evaluation-2	0-67
APACHE-II Estimated Mortality	Ln(R/l-R) = -3.517 + (APACHE-II × 0.146) + (Diagnostic Category Weight) + (0.603, only if post-emergency surgery)	0-100
SOFA	The Sequential Organ Failure Assessment	0-24
SOFA Estimated Mortality	Shown in Table 7.1	0-100

7.4 Results

7.4.1 Mortality according to SAPS-II and APACHE-II

Figure 7.1 shows APACHE-II scores and relative estimated mortality for the 104 patient days of data (R=0.98). Figure 7.1 also shows SAPS-II score and relative estimated mortality (R=0.96). It demonstrates a sigmoid relationship between mortality and patient severity score, as shown in [233]:

$$Estimated\ mortality = c/\ (1 + exp\ (-a \times (Severity\ Score - b))) \quad (7.4)$$

where for:

APACHE-II: a=0.15; b=24.09; c=1, and for

SAPS-II: a=0.10; b=50.36; c=0.94

This result is expected based on prior results and how these scores are calibrated to mortality. They thus confirm these patients are ‘typical’.

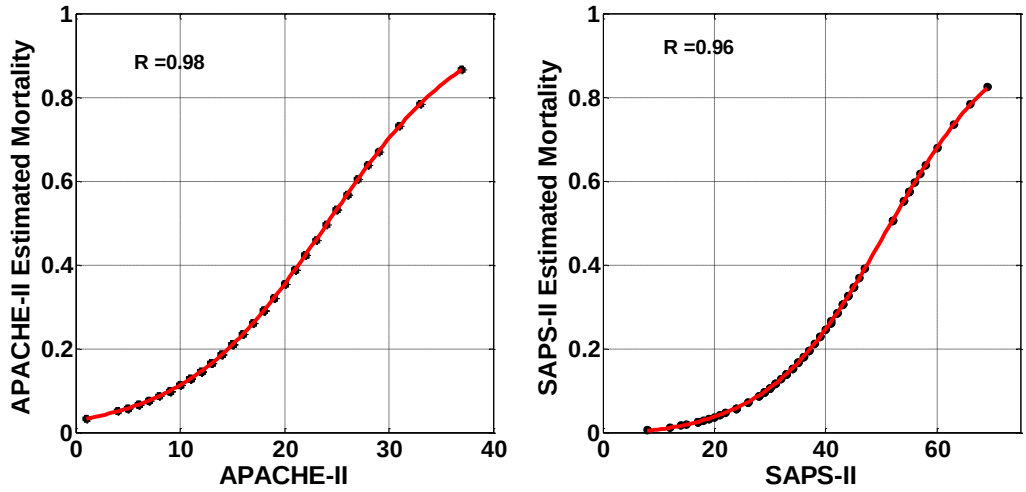


Figure 7.1: Left: APACHE-II scores and relative estimated mortality according to 104 patient days. Right: SAPS-II scores and relative estimated mortality. Both of them fit sigmoid relationship: mortality= c/ (1 + exp (-a*(Severity Score - b))).

7.4.2 Patient clinical results

Table 7.4 shows the average and median clinical results for each patient, including TISS-28, NEMS, APS, APACHE-III, SAPS-II, APACHE-II, and SOFA. In Table 7.4 (a), the lowest patient APACHE-III score is 7 (Patient 14, Trauma), and the corresponding TISS-28 score is 20 (the lowest). The highest APACHE-III is 87 (Patient 9, Resparitory Failure), while the corresponding TISS-28 score is 32 (not the highest). When a patient's TISS-28 is less than 25 points, the patient's illness is considered less severe. However, when TISS-28 > 25, it is hard to judge the severity of patient.

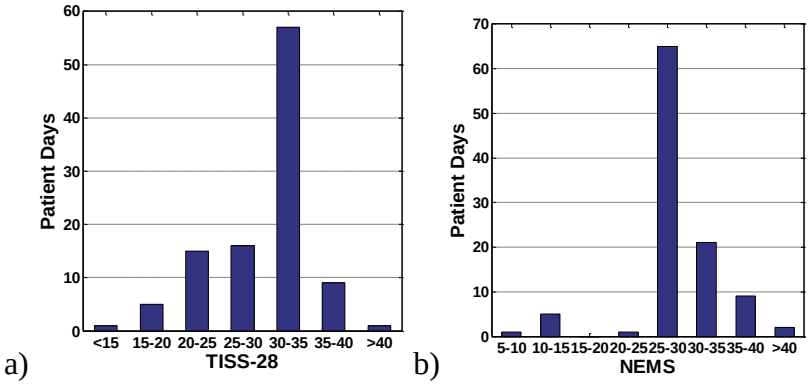
Figure 7.2 (a-g) shows patient clinical results based on all 104 patient days. For 57 out of 104 (55%) patient days, TISS-28 is between 30 and 35. For 65 out of 104 (62.5%) patient days, NEMS is between 25 and 30. The TISS-28 and NEMS resolution is not fine enough to differentiate different patient demands. APS, APACHE-III, SAPS-II, APACHE-II have better resolution to differentiate different patient severity at these levels.

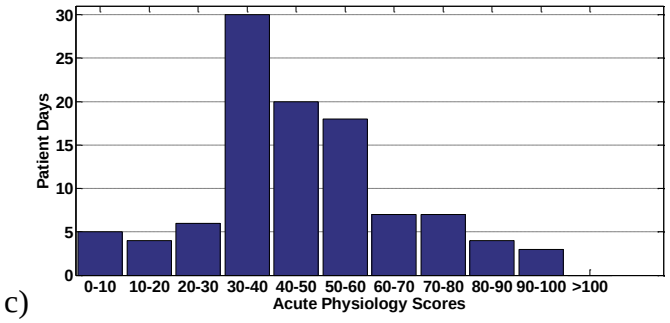
Table 7.**4(a):** 23 patients' *average* clinical results during their LOS

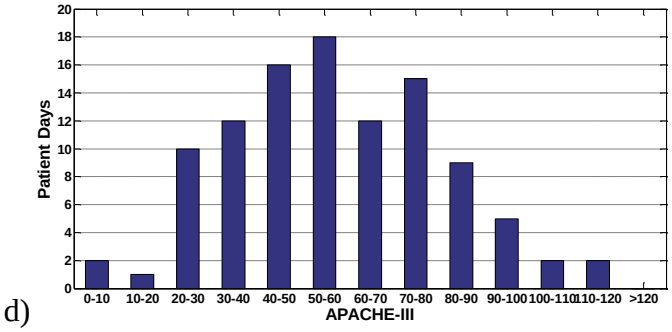
Patient	TISS-28 (78)	NEMS (66)	APS (252)	APACHE-III (299)	SAPS-II (163)	APACHE-II (67)	SOFA (24)
1	33	39	39	39	17	11	7
2	23	20	40	40	30	14	7
3	21	27	23	23	8	5	2
4	32	31	64	80	51	26	7
5	40	37	56	61	45	18	8
6	29	34	56	73	35	16	13
7	25	27	16	21	21	8	3
8	22	15	17	45	40	10	4
9	32	33	70	87	49	24	9
10	34	34	41	58	38	15	9
11	32	34	51	64	42	17	11
12	32	28	42	42	36	13	5
13	25	27	13	29	21	10	5
14	20	27	7	7	14	1	1
15	33	32	43	48	32	11	6
16	20	15	9	26	24	6	1
17	24	27	30	30	18	10	2
18	32	28	66	82	57	20	8
19	29	27	35	46	44	12	6
20	30	29	38	38	20	9	5
21	20	27	32	37	22	12	3
22	32	27	44	49	31	13	3
23	32	28	44	67	36	19	5

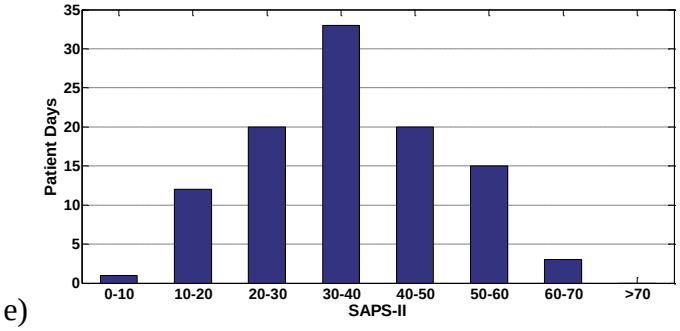
Note: The highest possible value for each nursing/severity score is given in brackets.

Table 7.5 shows the 5%, 25%, 75%, 95% percentiles and confident intervals (CI), median, and average of TISS-28, NEMS, APS, APACHE-III, SAPS-II, APACHE-II, and SOFA based on all 104 patient days. Table 7.6 shows the same results in Table 7.5 as percentages. These percentages are calculated with respect to the maximum possible score, for example, when TISS-28=33, its percentage result is 33/78=42.3% of the maximum. Figure 7.3 shows the cumulative distribution of patient clinical results in percentage, for all 104 patient days. Percentage results for TISS-28 and NEMS have much narrower 25%-75% CI, comparing with the other 4, APACHE-III, SAPS-II, APACHE-II, and SOFA.









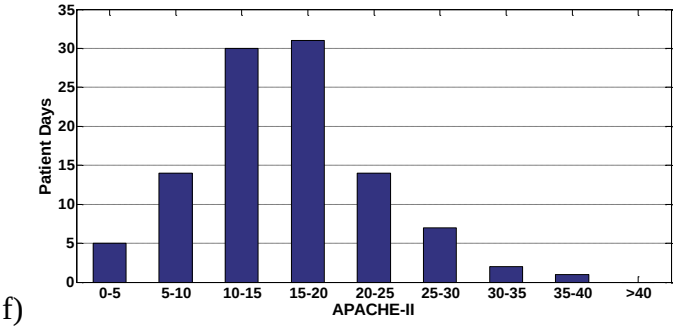
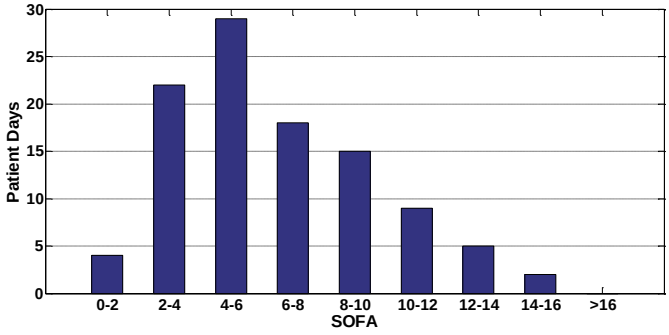


Figure 7.2 continued on next page

…Figure 7.2 continued



g)

Figure 7.2: TISS-28, NEMS, APS, APACHE-III, SAPS-II, APACHE-II, and SOFA distribution, based on 104 days patient data.

Table 7.**4(b):** 23 patients' *median* clinical results during their LOS

Patient	TISS-28 (78)	NEMS (66)	APS (252)	APACHE-III (299)	SAPS-II (163)	APACHE-II (67)	SOFA (24)
1	33	39	39	39	17	11	7
2	24	18	41	41	28	15	8
3	21	27	23	23	8	5	2
4	31	27	65	81	53	26	6
5	40	37	56	61	45	18	8
6	29	34	56	73	35	16	13
7	25	27	20	25	22	9	3
8	22	15	17	45	40	10	4
9	31	27	67	84	45	23	8
10	34	34	41	58	37	14	9
11	34	34	48	61	43	17	11
12	32	27	45	45	36	12	5
13	25	27	13	29	21	10	5
14	20	27	7	7	14	1	1
15	33	32	43	48	32	11	6
16	20	15	9	26	24	6	1
17	24	27	40	40	18	11	3
18	31	27	67	83	58	20	8
19	29	27	35	46	44	12	6
20	31	27	39	39	18	11	5
21	20	27	32	37	22	12	3
22	32	27	41	46	30	12	3
23	32	27	10	63	35	18	4

Note: The highest possible value for each nursing/severity scores is given in brackets.

Table 7.5**:** Clinical score results from 104 patient days.

	5% CI	25 %CI	Median	75% CI	95% CI	Average	SD (σ)
TISS-28 (78)	20	30	32	33	37	30	4.84
NEMS (66)	15	27	27	33	40	29	5.95
APS (252)	12	36	43	57	83	46	19.66
APACHE-III (299)	25	41	58	74	98	58	23.39
SAPS-II (163)	17	29	35	43	58	36	12.89
APACHE-II (67)	6	11	17	20	27	16	6.70
SOFA (24)	2	4	5	9	12	6	3.21

Note: The maximum clinical score is given in brackets.

Table 7.**6:** Clinical score results over 104 patient days (in percentage)

	5% CI	25 %CI	Median	75% CI	95% CI	Average
TISS-28 (78)	26	38	41	42	47	39
NEMS (66)	23	41	41	50	61	44
APS (252)	5	14	17	22	33	18
APACHE-III (299)	8	14	19	25	33	20
SAPS-II (163)	10	18	21	26	36	22
APACHE-II (67)	9	16	25	30	41	24
SOFA (24)	8	15	21	35	51	25

Note: The maximum clinical score is given in brackets.

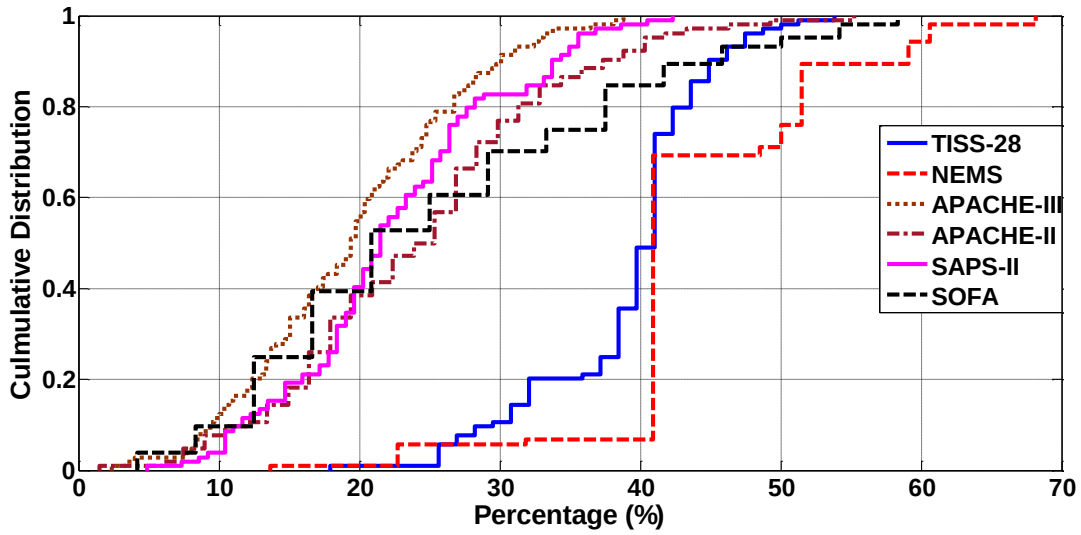


Figure 7.3: Cumulative distribution of patient clinical results (in percentage), based on 104 patient days. TISS-28 and NEMS have much narrower 25-75 CI, comparing with APACHE-III, SAPS-II, APACHE-II, and SOFA, as shown in Table 7.6.

7.4.3 Correlation between different patient clinical scores

Table 7.7 shows the correlation, R, values between different clinical scores. APS, APACHE-III, SAPS-II, and APACHE-II have strong correlation with each other (R > 0.8). TISS-28 has the strongest correlation with NEMS, as NEMS is a simplified TISS-28 score by definition. Correlation between TISS-28 and severity scores (R values are between 0.47 and 0.56) is stronger than NEMS (R values between 0.3 and 0.67). APACHE-III has a strong correlation between APS, SAPS-II, and APACHE-II. SOFA has moderate correlation to all other scores (R = 0.56-0.67).

Table 7.7: Correlation co-efficient, R, between different nurse workload and patient illness severity scores.

R	TISS-28 (78)	NEMS (66)	APS (252)	APACHE-III (299)	SAPS-II (163)	APACHE-II (67)	SOFA (24)
TISS-28 (78)	1	0.77	0.55	0.51	0.47	0.52	0.56
NEMS (66)	0.77	1	0.43	0.41	0.3	0.45	0.67
APS (252)	0.55	0.43	1	0.95	0.81	0.88	0.62
APACHE-III (299)	0.51	0.41	0.95	1	0.88	0.92	0.66
SAPS-II (163)	0.47	0.3	0.81	0.88	1	0.85	0.61
APACHE-II (67)	0.52	0.45	0.88	0.92	0.85	1	0.61
SOFA (24)	0.56	0.67	0.62	0.66	0.61	0.61	1

Note: The maximum possible clinical score is given in brackets.

7.4.4 Nurse-to-patient ratio prediction

Figure 7.4 (a-f) shows the correlation between TISS-28 score and NEMS, APS, APACHE-III, SAPS-II, APACHE-II, and SOFA. Besides NEMS, TISS-28 has moderate correlation with the other clinical scores (R = 0.47-0.56). Table 7.8 shows the equations to transfer each clinical score to nursing minutes from the data found. For example, if a patient has APACHE-III = 50, using the equation TISS-28 = 0.11 × APACHE-III + 23.93, it is possible to predict the required nursing minutes. The minimum required nursing minutes is 31.71 minutes/hour, so each APACHE-III point equals to 0.15 minutes/hour nursing time. For an APACHE-III score of 50, the total patient nursing demand is equal to 31.71+0.15×50=39.21

minutes/hour.

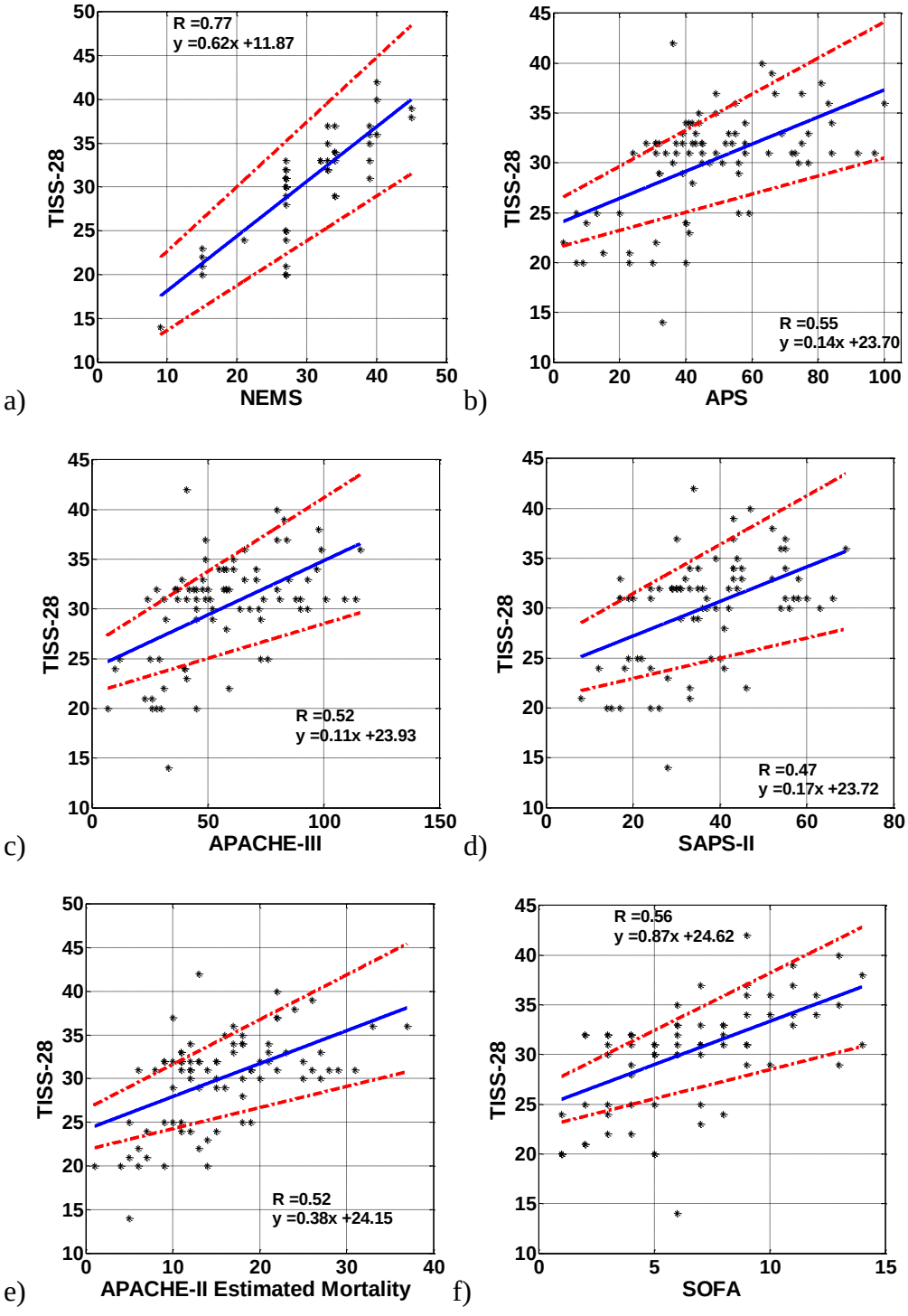


Figure 7.4: Linear regression between TISS-28 and other clinical scores. R values and equations are shown in each figure. Red chain lines represent 95% CI for coefficient estimation. Besides NEMS, all clinical scores have moderate correlation (R value between 0.47 and 0.56) with TISS-28. The minimum corresponding TISS-28 are all around 24 points, which suggests the minimum nursing time is 31.8 minutes/hour, roughly nurse-to-patient ratio equals 1:2.

Table 7.8: Correlation and correlation equations relating TISS-28 and other clinical scores. Basic nursing minutes is shown (around 31.8 minutes/hour), and each clinical point can be transferred to extra nursing minutes

Assessment tools	Equation	Median	Minimum Equivalent TISS point	Basic nursing minutes/hour	Extra minutes/hour·point
TISS-28 (78)	N/A	31	0	0	1.33
NEMS (66)	y=0.62x+11.87	27	11.87	15.73	0.82
APS (252)	y=0.14x+23.70	43	23.70	31.40	0.19
APACHE-III (299)	y=0.11x+23.93	52	23.93	31.71	0.15
SAPS-II (163)	y=0.17x+23.72	35	23.72	31.43	0.23
APACHE-II (67)	y=0.38x+24.15	14	24.15	32.00	0.50
SOFA (24)	y=0.87x+24.62	6	24.62	32.62	1.15

Note: 'x' represents different assessment tool's score, and 'y' represents the corresponding TISS-28 score. 'Median' is the median values based on 104 patient days. 'Basic nursing minutes/hour' means the minimum required nursing time when acuity score is 0. 'Extra minutes/hour·point' means the extra nursing time for each acuity point. For example, a patient with APACHE-III=50 points needs 23.9×10.6/8=31.71 basic nursing minutes/hour (one TISS-28 = 10.6 minutes/8 hours), and each extra point requires 0.11×10.6/8=0.15 minutes/hour, thus it requires 31.71+50×0.15=39.21 minutes/hour nursing care.

The minimum equivalent TISS-28 points are all around 24 (Table 7.8), except NEMS, which is 11.87. Thus, it is reasonable to set TISS-28=24 as the minimum patient nursing requirement for an 8-hour shift. The corresponding minimum nursing minutes is 24×10.6/8=31.8 minutes/hour, which roughly equals to a 1:2 nurse-to-patient ratio. This outcome suggests the absolute minimum nurse-to-patient ratio in ICU is 1:2. Clinically, however, TISS-28 was never observed to exceed 45 points, based on 104 patient days (Tables 7.5 and 7.6). As one nurse could look after a patient with TISS-28=45 points (24×10.6/8=59.6 mins/h), it is safe to set the maximum nurse-to-patient ratio in ICU as 1:1. The specific nurse-to-patient ratio should be adjusted between 1:2 and 1:1 according to specific patient scores across a unit.

7.4.5 Patient specific study

To further evaluate the performance of TISS-28, NEMS, APACHE-III, SAPS-II, APACHE-

II, and SOFA on each individual patient, 6 patients with LOS > 6 days were studied. Their changes in clinical scores with time are studied. Figure 7.5 shows these 6 patients daily change.

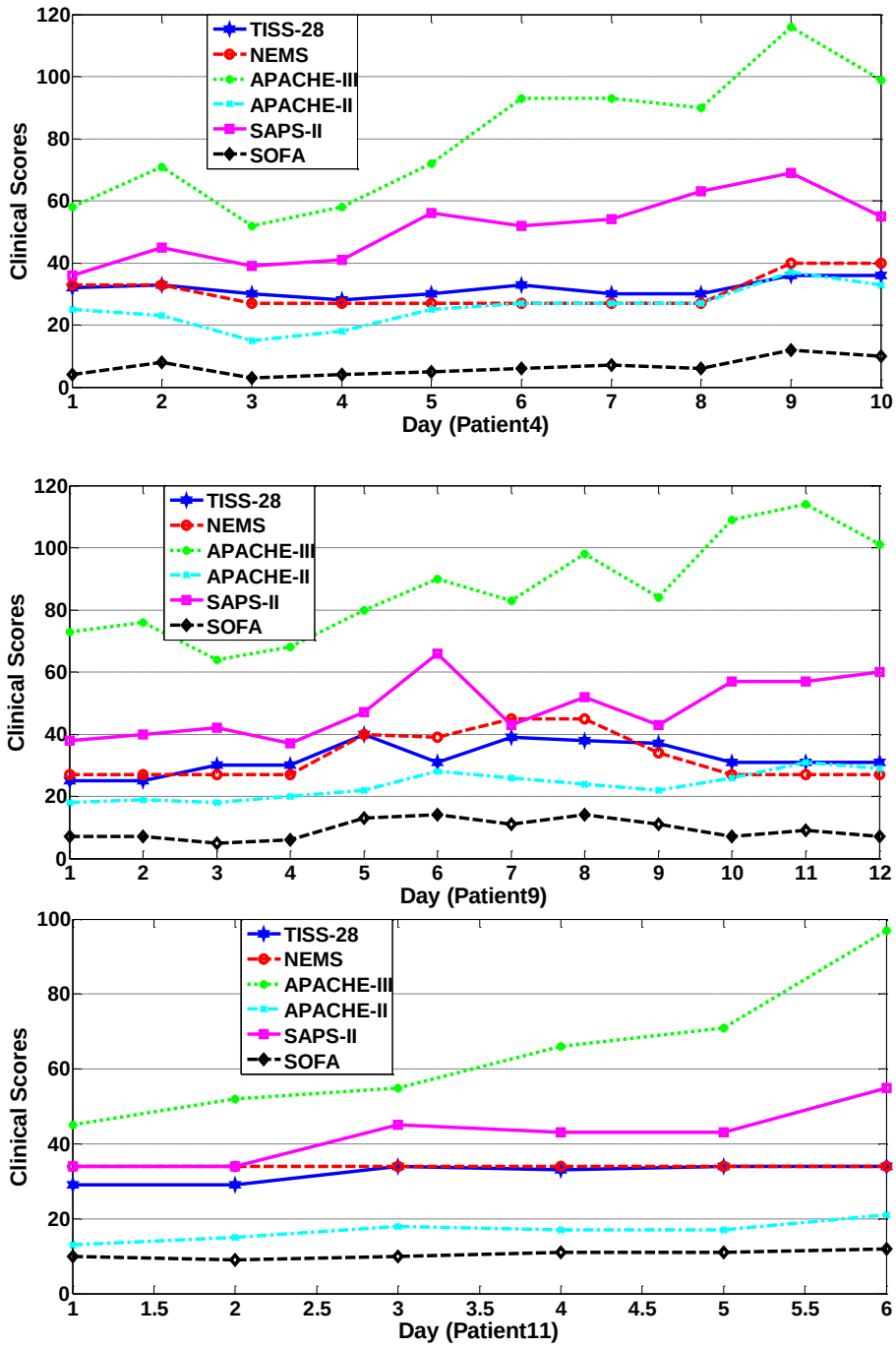


Figure 7.5 continued on next page

…Figure 7.5 continued.

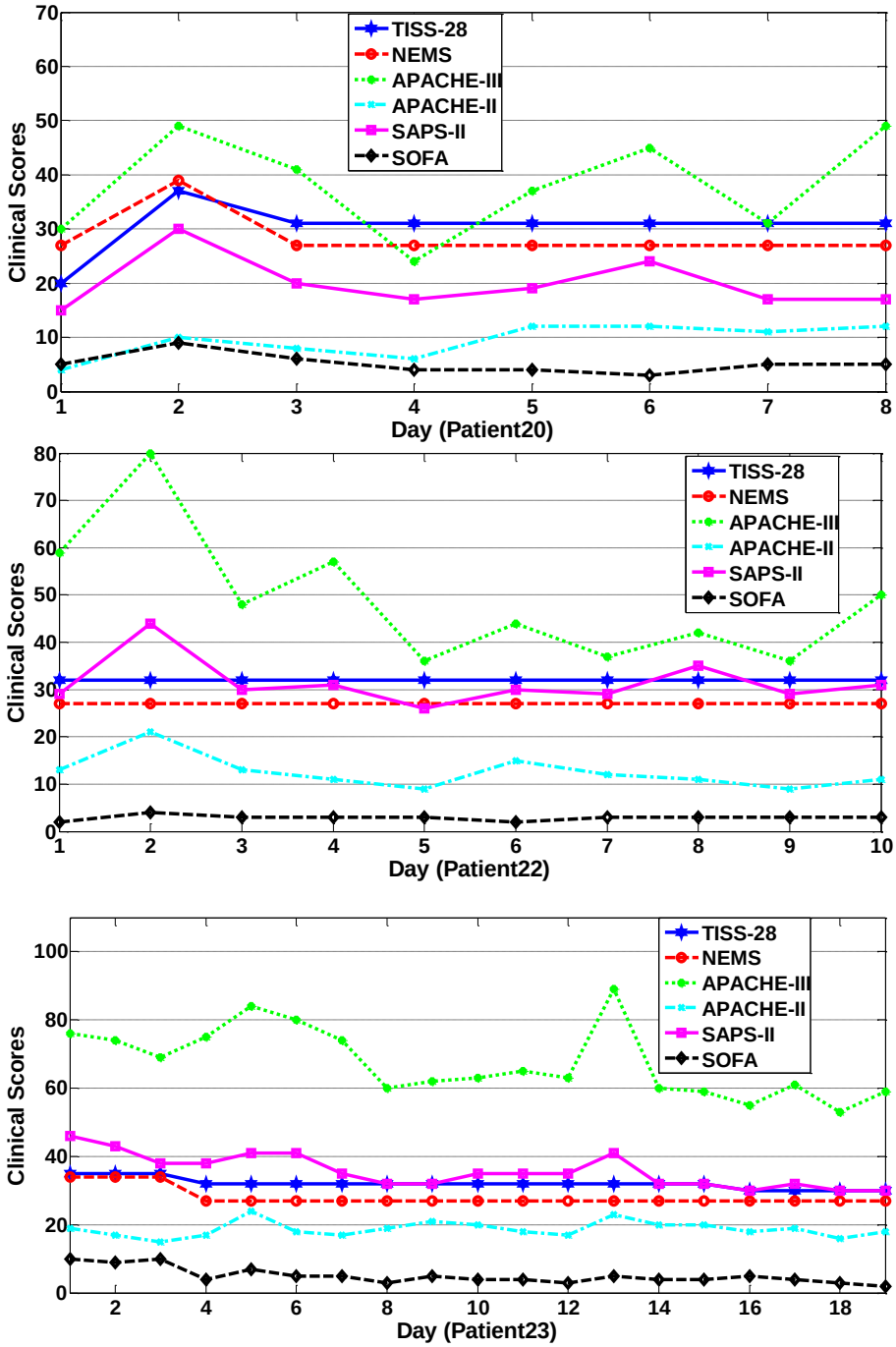


Figure 7.5: TISS-28, NEMS, APACHE-III, SAPS-II, APACHE-II, and SOFA scores over 6 patients during their LOS. Their LOS varies between 6 and 19 days.

Considering sickness severity, Patient 4, Patient 9 and Patient 11 showed an increasing trend in their APACHE-III and SAPS-II scores, which reflects their worsening condition over their stay. Patient 20 maintained a rather stable severity scale, as reflected by the APACHE-III and

SAPS-II scores. Patient 22 and Patient 23 showed a decreasing trend in their APACHE-III and SAPS-II scores. However, considering the workload assessment tools, TISS-28 and NEMS, none of the 6 patients had an apparent increasing or decreasing trend with respect to these scores or workload, showing significant insensitivity to workload as a function of severity.

APACHE-III score varied across a wide range of values in these patients. Hence, it can be used to describe patient sickness severity for a wide range of patients with the greatest resolution and/or sensitivity. Similarly, TISS-28 has better resolution than NEMS to describe nursing workload, as it captures more detailed work interventions being carried out by the nurses.

7.5 Discussion and limitations

7.5.1 TISS-28 and NEMS

During 104 patient days, TISS-28 scores calculated in this study never exceeded 45 points. TISS-28 scores ranged between 30 and 35 for 57 (55%) patient days. Thus, the resolution of the TISS-28 system does not adequately differentiate patient needs in the ICU. Table 7.9 shows TISS-28 items, points and whether each item is likely to change, based on patients admitted to the ICU.

As shown in Table 7.9, the sum of ‘Every patient’ and ‘Most patient’ is 5 items, 14 points, which means more than 95% of the patients would have at least 14 points during their entire LOS. The total score of ‘Barely happened’ and ‘Never happened’ is 11 items, 36 points, which means the highest TISS-28 score for more than 95% of patient days is 78-36=42 points. Thus, when TISS-28 is applied in clinical application, its value only varies between

14 and 42. In other words, only 12 out of 28 items tends to vary between patients, and only 36% of entire TISS-28 score band is used ((42-14)/78=36%), which can also seen in Figure 7.3. According to Figure 7.2 (a), TISS-28 scores were between 30 and 35 points for over 50% of patient days. Results in Table 7.5 and Figure 7.3 showed that interquartile range of TISS is 30-33 points, which is too narrow to differentiate different nursing workload. These results are further verified in patient specific study. For example, Patient 22's acuity has decreased during patient stay, but TISS-28 was constant at 32 points for all 10 days of stay.

NEMS is a simplified TISS-28, and it can range between 0 to 66 points. However, based on 104 patient days, patient NEMS scores have never exceed 45 points out of a possible 66 points. According to results in Figure 7.2 (b), there were 65 out of 104 days (62.5%) where NEMS ranged between 25 and 30. Specifically, over all these 65 days the NEMS score was equal to 27 points. According to Table 7.5, the IQR is 27-33 points, 5%-95% CI is 15-40 points, and only 25/66=38% of the entire score band is used. Thus, NEMS has even lower resolution than TISS-28 in this typical cohort. This result can also be seen in the patient-specific study. Patient 11's acuity increased and Patient 22's acuity decreased, but neither of their NEMS score changed during their entire stay.

7.5.2 APACHE-III, SAPS-II, APACHE-II and SOFA

APACHE-III can vary from 0-299. However, in reality, patient APACHE-III scores hardly exceed 120 points. Based on 104 days of clinical data, the highest APACHE-III score was 120 (40% of maximum value). It seems that it is very unlikely that a patient will obtain the highest score of each score sub-item. Of the 104 patient days of data, the IQR APACHE-III is 41-74 points and 5%-95% CI is 25-98 points. Even though the 25%-75% CI only covers 11% of the entire APACHE-III scale, APACHE-III has the highest standard deviation value ($\sigma =$

23.37) and its cumulative distribute has a more gradual slope (Figure 7.3). Thus, the APACHE III range and variability is wide enough to capture different patient acuity. In Figure 7.5, APACHE-III shows the most obvious change compared to other patient severity assessment tools.

SAPS-II ranges from 0 to 163 points. During 104 patient days, SAPS-II scores never exceed 70 points (43% of maximum value), as patients are unlikely to obtain the highest score for each item. According to Figure 7.2 (e), SAPS-II also showed a Gaussian distribution shape, with mean of 36 point and standard deviation $\sigma = 13.89$. Table 7.5 shows SAPS-II IQR is 29-43 points and the 5%-95% CI is 17-58 points. In this cohort, it has shown good performance in evaluating patient acuity as SAPS-II has higher resolution. In Figure 7.5, Patient 4, Patient 9, and Patient 11 SAPS-II values have an increasing trend, and Patient 23 has a decreasing trend, while Patient 20 and Patient 22 maintain the same SAPS-II level. SAPS-II values also show a strong correlation with APACHE-III, suggesting higher resolution in capturing patient-specific condition is eminent in both scores.

APACHE-II ranges from 0 to 67 points. Based on 104 patient days' clinical data, patient APACHE-II never exceeded 40 points (60% of maximum value). According to Figure 7.2 (f), the APACHE-II distribution is Gaussian, with mean of 16 points and standard deviation $\sigma = 6.7$. Table 7.5 shows the APACHE-II IQR is 11-20 points and 5%-95% CI is 6-27 points. Its resolution is lower than APACHE-III and SAPS-II in differentiating patient acuity level. Even though APACHE-II has a strong correlation with APACHE-III (R=0.92), APACHE-II cannot capture patient-specific severity trends as sensitive as APACHE-III.

Table 7.9: TISS-28 items, points, how many patient days are counted, percentage, and whether each item is likely to change

	TISS-28	Points	Days	Pct. (%)	Whether each item is likely to change?
1	Standard monitoring. Hourly vital signs, regular registration and calculation of fluid balance.	5	104	100	Every patient
2	Laboratory. Biochemical and microbiological investigations.	1	100	96.2	Most patients
3	Single Medication, any route (IV, PO, IM, etc.).	2	1	1	Barely occurred
4	Multiple intravenous medications (more than 1 drug, single shots, or continuously)	3	103	99	Most patients
5	**Routine dressing changes. Care and prevention of decubitus and daily dressing change)**	**1**	**92**	**88.5**	**Depends on patient, Common**
6	**Frequent dressing changes (at least one time per each nursing shift) and /or extensive wound care**	**1**	**13**	**12.5**	**Depends on type of diagnosis**
7	Care of drains. All (except gastric tube)	3	104	100	Every patient
8	**Single vasoactive medication. Any vasoactive drug.**	**3**	**22**	**21.2**	**Depends on patient diagnosis**
9	Multiple vasoactive medications. More than 1 vasoactive drug, disregard type and dose.	4	2	1.9	Barely occurred
10	Intravenous replacement of large fluid losses. Fluid replacement >3 liters per square meter per day, disregard type of fluid administered.	4	0	0	Never occurred
11	**Peripheral arterial catheter**	**5**	**92**	**88.5**	**Depends on patient, common**
12	Left atrium monitoring. Pulmonary artery floatation catheter with or without cardiac output measurement.	8	0	0	Never occurred
13	**Central venous line**	**2**	**82**	**78.8**	**Depends on patient, common**
14	Cardiopulmonary resuscitation after arrest in the last 24 hours (single precordial percussion is not included)	3	2	1.9	Barely occurred
15	**Single specific interventions in the ICU. intubation, introduction of a pacemaker, cardioversion, endoscopies, emergency surgery in the past 24 hours, gastric lavage.**	**3**	**6**	**5.8**	**Intubation could happen. The rest never occurred.**
16	Multiple specific interventions in the ICU. More than one, as described above.	5	0	0	Barely occurred
17	Specific interventions out of ICU. Surgery or diagnostic procedures.	5	3	2.9	Barely occurred
18	**Mechanical Ventilation. (Any form of ventilation or assisted ventilation with or without PEEP; with or without muscle relaxants; spontaneous breathing with PEEP**	**5**	**97**	**93.3**	**Depends on patient, common**
19	Supplementary ventilator support	2	0	0	Never occurred
20	**Care of artificial airways. Endotracheal tube or tracheostoma**	**1**	90	86.5	**Depends on patient, common**
21	**Treatment for improving lung function. Thorax physiotherapy, incentive spirometry, inhalation therapy, intratracheal suction.**	**1**	70	67.3	**Depends on patient**
22	**Hemofiltration techniques. Dialytic techniques.**	**3**	**9**	**8.7**	**Depends on patient, uncommon**
23	Quantitative urine output measurement.	2	100	96.2	Most patients
24	Active diuresis (eg. Furosemid >0.5mg/kg/day for overload.)	3	6	5.8	Barely occurred
25	Measurement of intracranial pressure (ICP)	4	0	0	Never occurred
26	Treatment of complicated metabolic acidosis/ alkalosis	4	0	0	Never occurred
27	**Intravenous hyperalimentation**	**3**	**26**	**25**	**Depends on patient**
28	**Enteral feeding. Through gastric tube or other GI route (eg. jejunostomy)**	**2**	58	55.8	**Depends on patient**

Notes: 'Every patient' means the relative treatment is applied to every patient day. 'Most patients' means the relative treatment is applied for more than 95% patient days. 'Barely occurred' means the relative treatment is less than 5% patient days. 'Never occurred' means the relative treatment is extremely rare in Christchurch Hospital and was not observed in this data set. 'Depends on patient' items are high-lightened, which means the relative treatment varied from patient to patient. There are only 12 items are categorised as 'Depends on patient'

SOFA ranges from 0 to 24 point. As SOFA is designed to assess patient acuity according to 6 major organ failures, it is very unlikely a living patient suffers all 6 organ failures to a peak or near peak level. Thus, the highest SOFA score observed in this study is 14 points (58% of maximum value). In Figure 7.2 (g), SOFA is Gaussian with a mean of 6 points and standard deviation of $\sigma = 3.21$. Table 7.5 shows SOFA IQR is 4-9 points and 5%-95% CI is 2-12 points. Its resolution is the lowest among all acuity scores. SOFA also has a weaker correlation with APACHE-III, SAPS-II and APACHE-II, as shown in Table 7.7. Of the 6 days analysed in Figure 7.5, only Patient 4's SOFA values have an increasing trend. Patient 9, Patient 11, Patient 20, Patient 22, and Patient 23 maintained the same SOFA level, which means it is difficult to assess varying patient using SOFA score.

7.5.3 Correlation between TISS-28 and patient acuity

As discussed, it is reasonable to use APACHE-III as the best tool to assess patient acuity level, and use TISS-28 as the better tool to assess nursing workload. Figure 7.4 shows that TISS-28 has a moderate correlation with APACHE-III, SAPS-II, APACHE-II, and SOFA (R ranges from 0.47 to 0.56). Thus, it is also possible to use acuity assessment tools to predict nursing workload and nurse-to-patient ratio. Table 7.8 shows the equations to predict nursing workload according to APACHE-III, SAPS-II, APACHE-II, and SOFA scores. The basic nursing workload for a minimum effort patient is equivalent to TISS-28=24 points, which is 31.8 minutes/hour. Each extra acuity point can be transferred to extra nursing minutes. Meanwhile, the required nurse-to-patient ratio is predicted by this data to vary between 1:2 and 1:1.

However, because TISS-28 lacks sensitivity, the TISS-28 scores may not follow changes in APACHE-III very well. As shown in Figure 7.5, an obvious increase and decrease in acuity

level cannot be captured using the TISS-28 curves, which are relatively flat. There are 2 main reasons that cause the mismatch between TISS-28 and APACHE-III:

1. If a patient has long stay in ICU, the chances that they require dialysis increase dramatically. Patients receiving dialysis will see an improvement in patient physiology, resulting in a big drop on their APACHE-III scores. In contrast, the patient TISS-28 and NEMS score increases due to points associated with dialysis, which does not necessary relate to the intensity of the workload.
2. Patient sedation level is an important factor influencing APACHE-III and SAPS-II reports, as sedation level can cause a 48 points (16% of maximum value) difference in APACHE-III score. In addition, patients in ICU can change from a fully conscious state to a totally sedated level within few hours, causing their APACHE-III to change dramatically. However, the patient sedation level does not influence patient TISS-28 score. Thus, sedation level can cause significant changes in APACHE-III score, that are not captured in TISS-28.

Thus, a range of factors contribute to nurse workload, and while the severity of patient illness is a moderate indicator of required care, it is not sufficient to totally capture patient-specific nursing workload requirements.

7.5.4 Limitation

There are some limitations in this study:

1. Only 23 patients and 104 days are included in this research. Their LOS varied from 1 to 23 days. This database may not be general enough to generate TISS-28, NEMS, APACHE-III, SAPS-II, APACHE-II, and SOFA distribution results that adequately represent a full ICU cohort, as shown in Figure 7.2 and Table 7.2. More patients can

be included in future study. However, the ranges seen here are typical for this ICU [271].

2. This research utilizes data from an adult ICU where the patient TISS-28 score never exceeds 45 points within 104 patient days. The lack of sensitivity of TISS-28 to patient acuity needs to be verified over a range of ICU types, and over a range of hospitals, before results can be more widely generalized from this predominantly medical ICU.

7.6 Summary

This chapter describes different patient severity and nursing workload assessment for 23 patients, 104 patient days. It was found that the APACHE-III and SAPS-II have better resolution to describe patient acuity compared to APACHE-II and SOFA. TISS-28 has better resolution to describe nursing workload than NEMS. However, both TISS-28 and NEMS display poor sensitivity to different patient-specific nursing demands. The reason for TISS-28's poor performance is that only 12/28 items, totaling 28/78 (36%) of TISS-28 score, varies from patient to patient. TISS-28 has a moderate correlation with APACHE-III, SAPS-II, APACHE-II, and SOFA, and it is possible to use patient severity scores to predict nursing requirement and corresponding nurse-to-patient ratio.

In the next chapter, patient sedative condition will be analyzed by using different types of assessment tools. Nursing workload will be calculated using the CATS. The correlation between nursing workload and patient sedative condition will be presented, to demonstrate the influence of patient sedative condition over patient nursing demands.

Chapter 8 Patient Sedative Conditions and its Relation with Nursing Interventions

Patients are frequently sedated in the ICU to enable recovery from an underlying illness [272-275]. Several tools exist to evaluate patient sedation level, such as the Richmond Agitation-Sedation Scale (RASS), which was developed by physicians, nurses and pharmacists [276, 277]. The Glasgow Coma Score (GCS) is a neurological scale that aims to give a reliable, objective way of recording the conscious state of a person for initial and subsequent assessment [278]. However, it may not represent patient sedation level well [279, 280].

In addition, sedated patients are typically more ill and require more intensive care. However, it is possible that the direct nursing demand decreases due to less communication between nurse and patient. Virtually no research has examined the correlation between patient sedation level and patient nursing demand.

8.1 Introduction

There are several different methodologies to evaluate patient sedation level. One of them is the APACHE-III sub-section ‘neurologic abnormalities’, as presented in Appendix 7.1. It evaluates patient sedation level based on patient’s eye response, verbal ability, and motor reaction. The score ranges from 0 to 48 points, with higher scores reflecting higher patient sedation.

The Glasgow Coma Scale (GSC) [278] assesses the conscious state of a person by evaluating patient eye, verbal, and motor response. Eye response ranges from 1-4 points; verbal response

ranges from 1-5 points, and motor response ranges from 1-6 points, giving a total score of 3-15 points, where higher scores reflect lower sedation. It is widely used in ICU to give a quick evaluation of patient sedation level.

The Richmond Agitation and Sedation Scale (RASS) [281, 282] ranges from -5 to +4 points. From 0 to +4 means the patient is alert, restless, or agitated, and -1 to -5 indicates increasing sedation. It thus assesses agitation (positive values) and sedation (negative values) levels.

These sedation assessment tools provide quick evaluations of patient sedation level. RASS and GSC have been well studied [281, 283-286]. However, some studies, such as Gill et al. [280], showed the GSC is not accurate enough to describe actual patient condition, as the bias and variability are high. Heron et al. [279] also shows that GCS assessment accuracy is low, especially with respect to eye and motor assessment. Overall, GSC has been found to lack robustness and reliability [287-292].

In this study, patients included in the CATS monitoring study had their GSC and RASS score, as used in the Christchurch Hospital ICU, evaluated alongside CATS nursing intervention time. In addition, sedation delivery is also compared, giving an objective evaluation of the relationship between the quantity of sedative drug with GSC, RASS and CATS scores.

This chapter first validates the performance of GCS and RASS. It then compares patient sedation levels between day and night. Finally, it examines the correlation between patient sedation level and CATS evaluated nursing workload.

8.2 Data collection

Patient-specific GCS and RASS were recorded for all CATS study patients, in 2-6 hour intervals, depending on patient condition. If GSC or RASS are not recorded at a specific hour, the nearest previous recorded GSC or RASS is used. Thus, if a patient GSC score is 10 points at 5 am and 13 points at 10 am, the GSC score from 6 am to 9 am are also evaluated as 10 points.

In the ICU setting, the primary sedative drugs used are propofol, fentanyl, morphine benzodiazepines, and dexmedetomidine [293, 294]. In the Christchurch Hospital ICU, propofol and fentanyl are the most commonly used sedation drugs. The sedative drug dose usage was recorded hourly on the 24-hour chart. The concentration of propofol used in practice is 10 mg/ml and the concentration of fentanyl is 20 mcg/ml. In this research, each sedation drug dose is defined as 1 unit = 10 mg propofol or 1 unit = 20 mcg fentanyl, equalling 1 ml of infusion delivery. For example, if a patient is given infusion of 10ml propofol/hour and 5ml fentanyl/hour, the sedation drug dose is 15 units/hour.

In this research, 23 patients who occupied Bed 7 are included, covering 104 patient days, within which 14 patients were given sedative drugs covering 69 patient days. Further, 12 patients stayed in Bed 7 for more than 3 days, covering 89 patient days and 10 of these patients received sedative drugs for more than 1 day, covering 65 patient days. This data is also shown in Table 8.1. Patient cohort in this analysis is thus chosen according to specific scenarios in Table 8.1.

8.3 Validation of GSC and RASS

8.3.1 Correlation between RASS and GCS

To assess correlation between RASS and GCS, all patients included in the CATS trial were selected (Patient Group A), the patient-specific average RASS and GCS scores for day (7am-11pm), night (11pm-7am), and 24-hour were compared. Each hour, a patient was given a 'high RASS score' (score for most awake period) and a 'low RASS score' (score for most sedated period), and the low RASS score of each hour was used to describe patient condition in terms of sedation level, where lower values, even if positive, describe greater sedation level.

Table 8.1: Different patient groups based on their LOS in 'Bed 7' and sedative drug dosage

Group Number	Group Description	Number of Patient	Patient Days
A	All Patients	23	104
B	Patients who received sedative drugs	14	69
C	Patients who stayed at Bed 7 for more than 3 days	12	89
D	Patients who received sedative drugs for more than 1 day	10	65

Figure 8.1 shows the distribution of GCS in terms of different RASS points based on all 104 patient days, 2496 patient hours. In this study, only 20 hours of RASS = +1 were recorded and patient 'low RASS score' never exceeded +1 point. Thus, patients with RASS score equal to +1 and 0 are combined in the distribution plot for simplicity relative to sedation level. Patient hours are shown at the bottom of each box for each level. Figure 8.2 shows the correlation between average RASS scores and corresponding average GCS scores for day, night, and 24-hour, based on all 104 patient days.

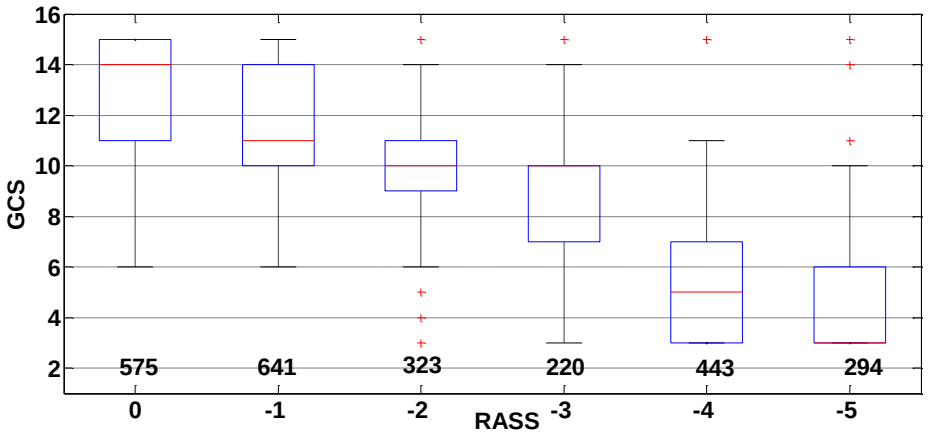


Figure 8.1: Distribution of GCS on different RASS points based on 104 patient days, 2496 patient hours. Patient hours are demonstrated at the bottom of each box. The GCS for RASS = 0 and +1 are combined into a single box.

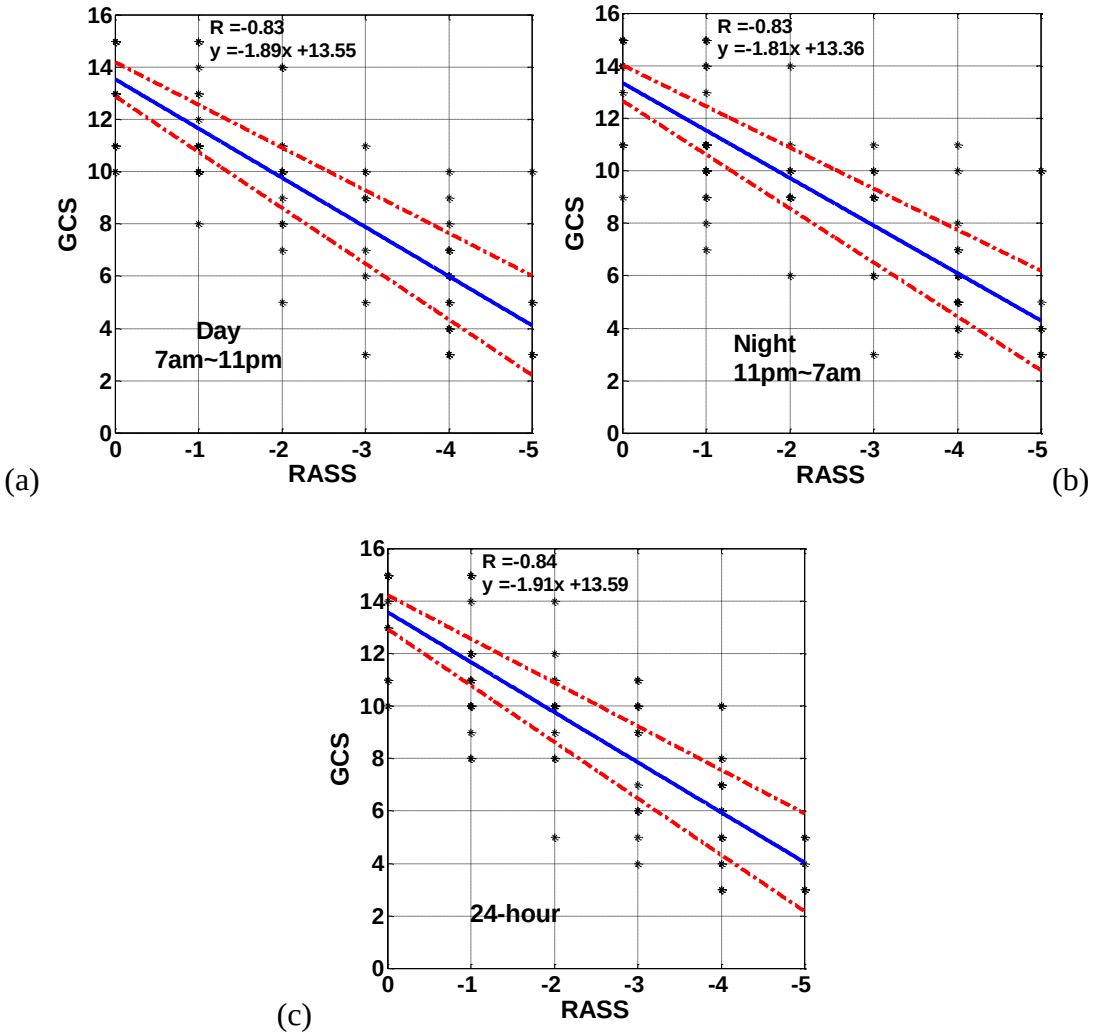


Figure 8.2: Correlation between RASS and GCS over the a) day, b) night, and c) entire 24-hour, based on 104 patient days. A more negative RASS and lower GCS reflect increased sedation. The dashed lines represent the 95% CI.

Figure 8.2 shows a strong negative correlation between RASS and GCS (R=-0.83, -0.83, and -0.84 for day, night, and 24-hour), as expected. Note that greater sedation level is more negative (-5) for RASS and lower (3) for GCS. Figure 8.1 also shows GCS scores have statistically significant difference between different RASS groups (all $p<0.005$ with Ranksum test). This strong correlation is understandable, because both RASS and GCS scores are subjective, evaluated by the same nurse at the same time. Thus, bias could simultaneously happen for both RASS and GSC, but will be equivalent. Therefore, it is necessary to validate RASS and GCS against sedation drug dose, where more drug dosage should, in general, be correlated to greater sedation level.

8.3.2 Correlation between RASS and sedative drug dose

Within the 104 patient days, 14 patients (Patient Group B) who received sedation drugs were selected, covering 69 patient days (66.3%). Figure 8.3 shows the distribution of these 69 patient days (1656 hours) sedative drug dose on different RASS points. RASS scores of +1 and 0 were combined again. Figure 8.4 shows the correlation between average RASS score of each day and corresponding average drug dose for day, night, and 24-hour, for this patient group.

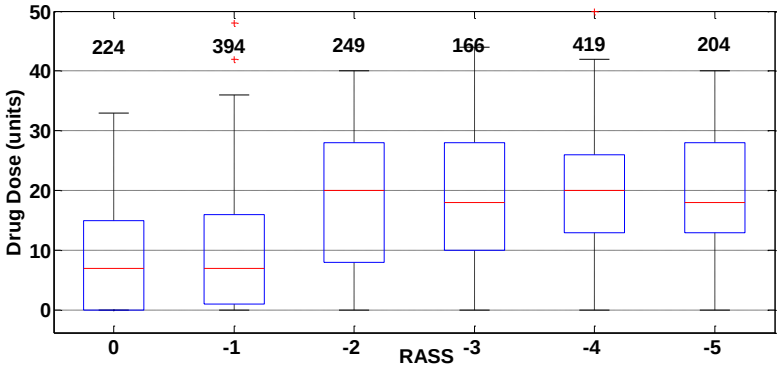


Figure 8.3: Distribution of sedative drug dose on different RASS points for Patient Group B. Patient hours are demonstrated at the top of each box. RASS scores of 0 and +1 were combined into a single box plot.

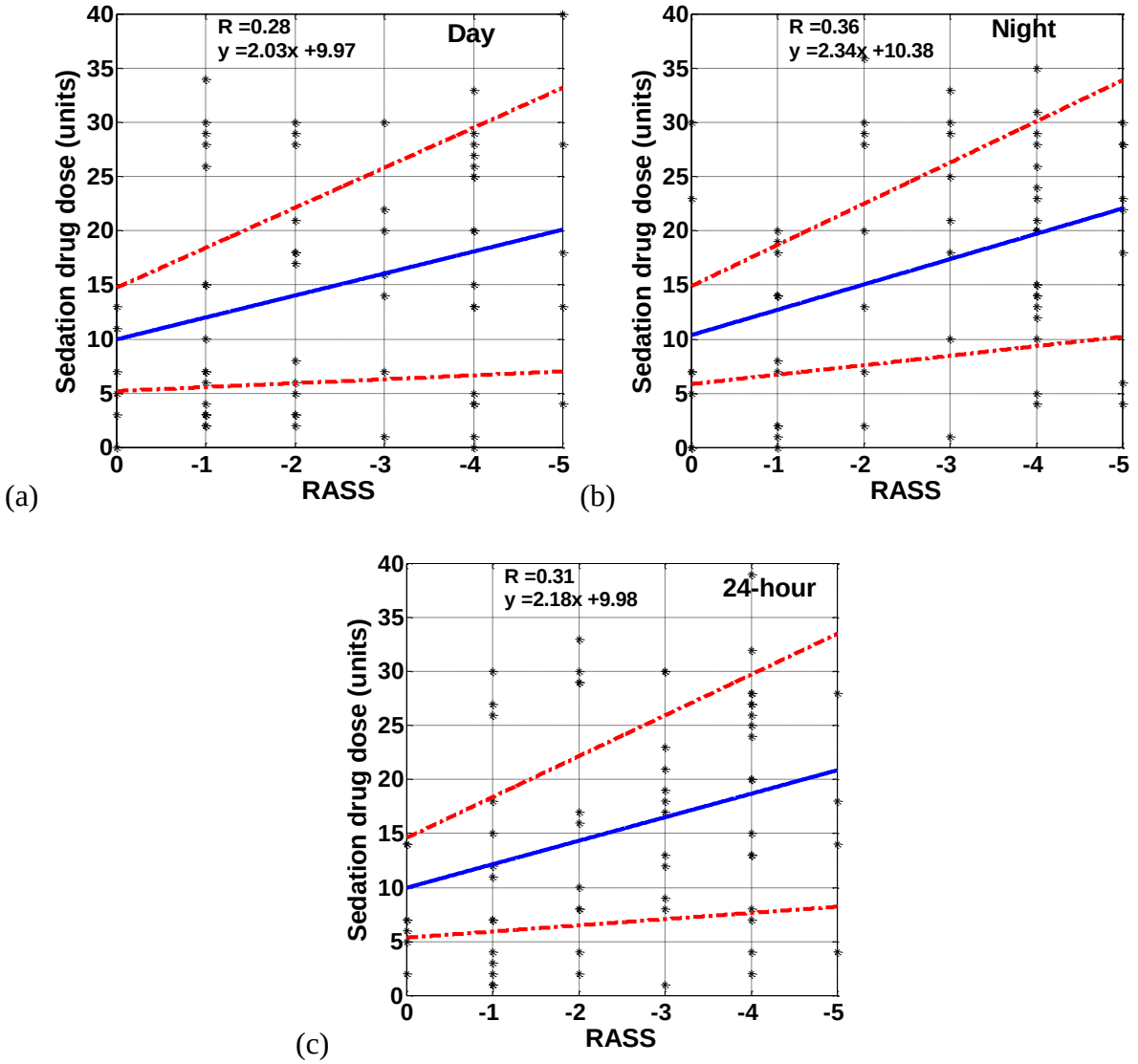


Figure 8.4: Correlation between RASS and drug dose during the a) day, b) night, and c) entire 24-hour, for Patient Group B. The dashed lines represent the 95% CI.

Low to moderate correlations between RASS and sedative dose were found in Figure 8.4, with R=0.28, 0.36, 0.31 for day, night, and entire 24-hour period respectively. When RASS score is higher (0 and -1), the patient tends to receive less sedation, as expected. Figure 8.3 shows that when patient RASS score is low (-2 ~ -5), the patient receives significantly more sedative drug (20 units/hour, $p<0.001$), also as expected. However, drug dose is only weakly correlated with RASS with very large CI bands, showing other factors have an influence.

This result occurs in part because using RASS scores distinguish sedation level can be difficult and/or subjective. Attending nurses are very likely to have no difficulty in identifying the difference between alert patients (RASS=0 or -1) and unconscious patient (RASS= -2~-5) , but it can be much more difficult to identify the differences among unconscious (RASS= -2~-5) or alert conditions (RASS= 0 or -1). This lack of objective has also been reported elsewhere [295].

8.3.3 Correlation between GCS and sedation drug dose

Figure 8.5 shows the distribution of sedative drug dose for different GCS scores for Patient Group B, spanning 69 patient days. The cohort is divided into 4 groups based on GCS: 3-5, 6-8, 9-11, and 12-15. Each of these groups can represent a different sedation level. Figure 8.6 shows the correlation between average GCS per day and corresponding drug dose, for each of the day, night, and 24-hour.

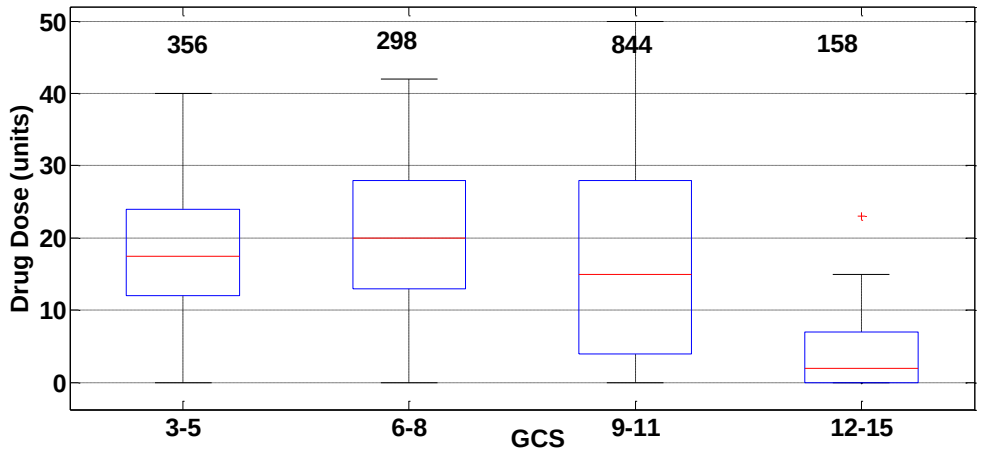


Figure 8.5: Distribution of sedative drug dose on different GCS points for Patient Group B. Patient hours are shown at the bottom of each box.

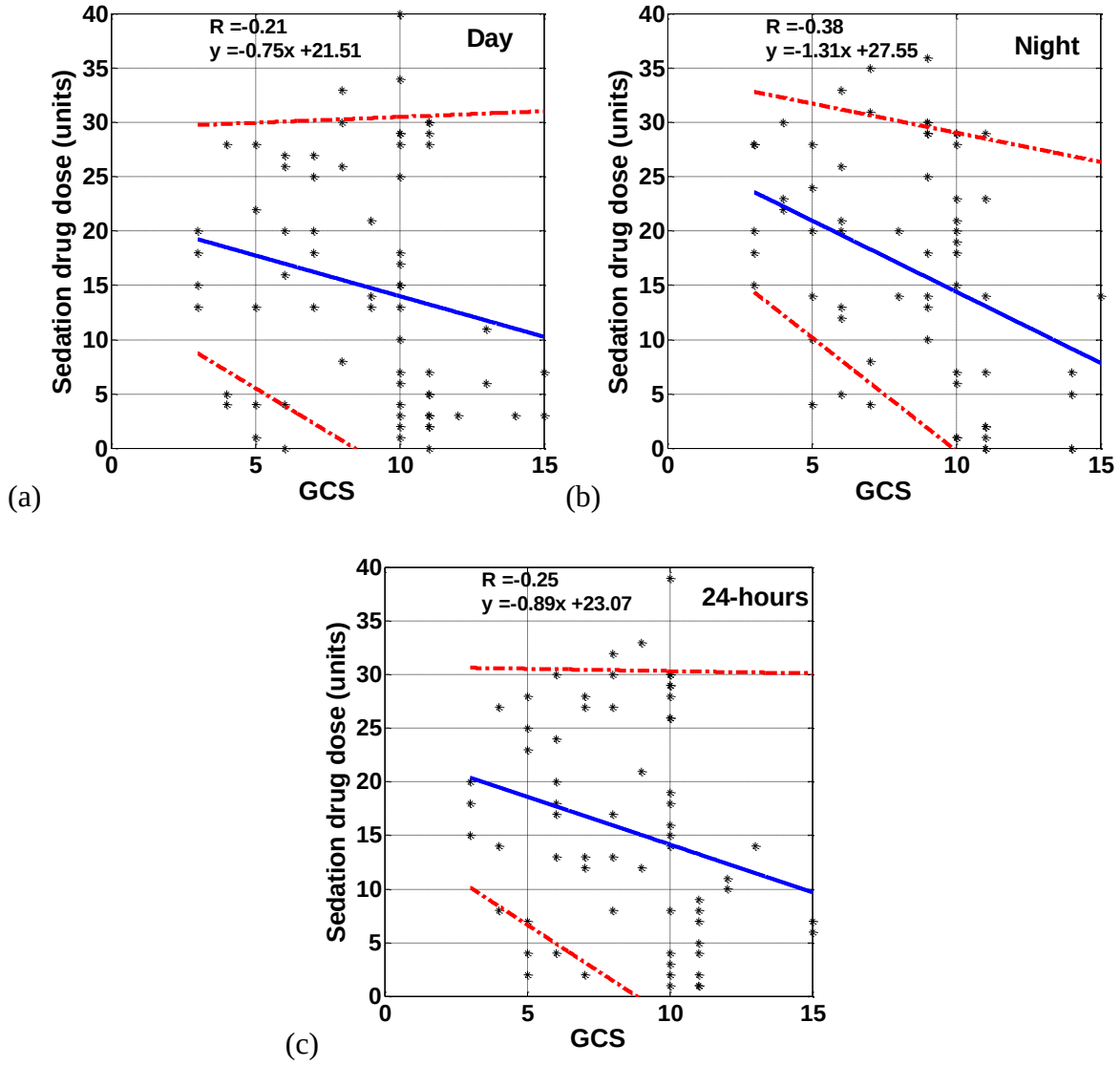


Figure 8.6: Correlation between GCS and drug dose during a) day, b) night, and c) entire 24-hour for Patient Group B. The red dashed lines show the 95% CI range.

Figure 8.6 shows low to moderate correlation between GCS and sedative drug dose (R=-0.21, -0.38, and -0.25 for day, night, and 24-hour periods respectively). When GCS is high (12-15 points), patients tend to receive less sedation, as expected for more alert patients. The same result is evident in Figure 8.5 with significant variability. When GCS score increases, drug dosage tends to decrease, as expected. However, the CI range in Figure 8.6 is very large and matches the weak correlations seen. Hence, in Figure 8.5 there is only a statistically significant difference between GCS = 12-15 and other 3 groups GCS = 3-11, $p < 0.001$ with Ranksum test.

Figures 8.5 and 8.6 show that GCS score is lower when patients receive high sedative doses. However, when the patient received lower drug dose (less than 15 units/hour), it is comparatively difficult to predict the patient GCS score. Patient response to the sedative drug is patient-specific. Hence, it is more variable when the sedative dosage is lower. Equally, a low GCS score can also be due to unrelated clinical factors or illness as well.

In summary, RASS and GCS have strong correlations so they could both be used to quickly give a general evaluation of patient sedation level. However, both RASS and GCS may not accurately represent patient sedation level, which makes their use in this study difficult. In particular, both RASS and GCS have only low to moderate correlation with patient sedative drug dose. Hence, the variability observed requires another metric.

8.4 Sedation level during day and night

8.4.1 RASS 24-hour distribution

Figure 8.7 shows patient 24-hour average RASS distribution per hour. Patient group C is selected as the cohort, covering 89 patient days, with LOS more than 3 days. This group is selected because patients with LOS>3 days may have more reliable RASS scores, while patient with LOS<3 days may not have RASS evaluated routinely. Figure 8.7 shows that patients appear to be less sedated from 12:00 – 21:00 hours (median RASS = -1), than during the rest of the day (median RASS = -2). In addition, it shows patient day (7am – 11pm) and night (11pm - 7am) average RASS distribution. The median of day RASS score is -1 and for the night it is -2. However, no significant statistical difference was found ($p=0.25$), and the distribution are relatively constant.

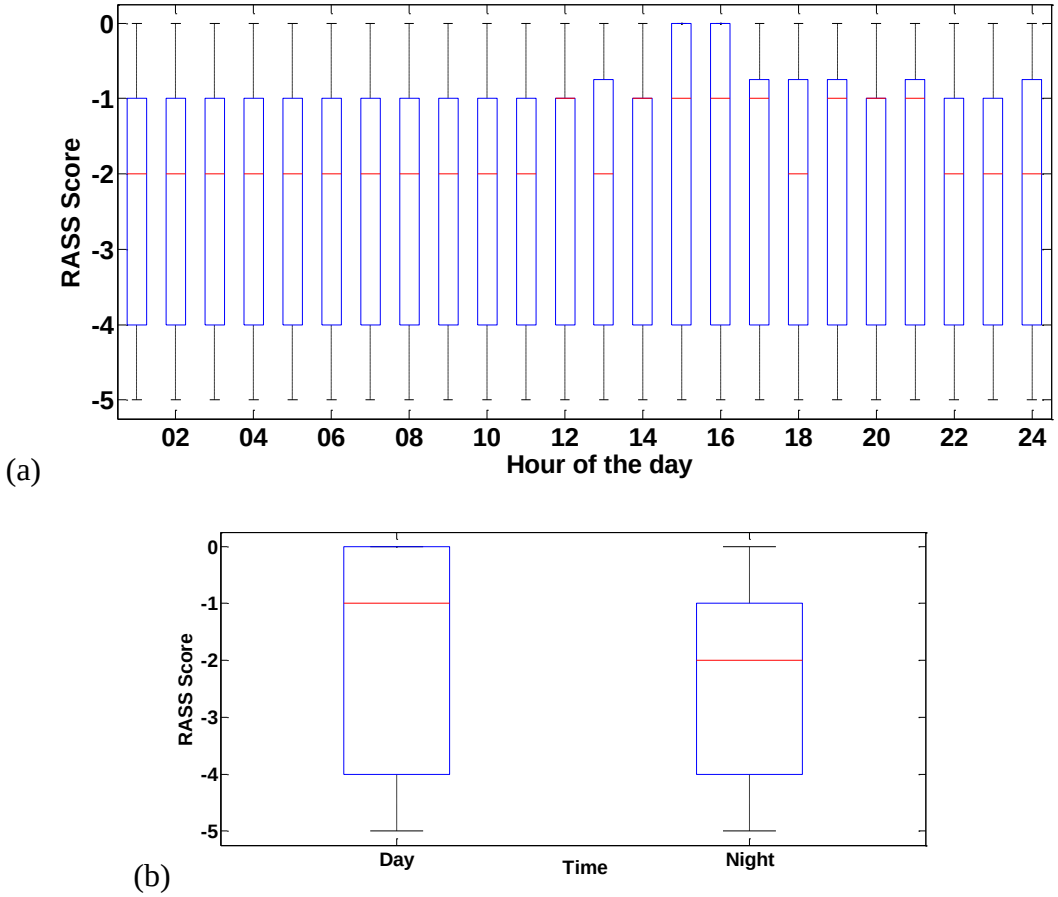
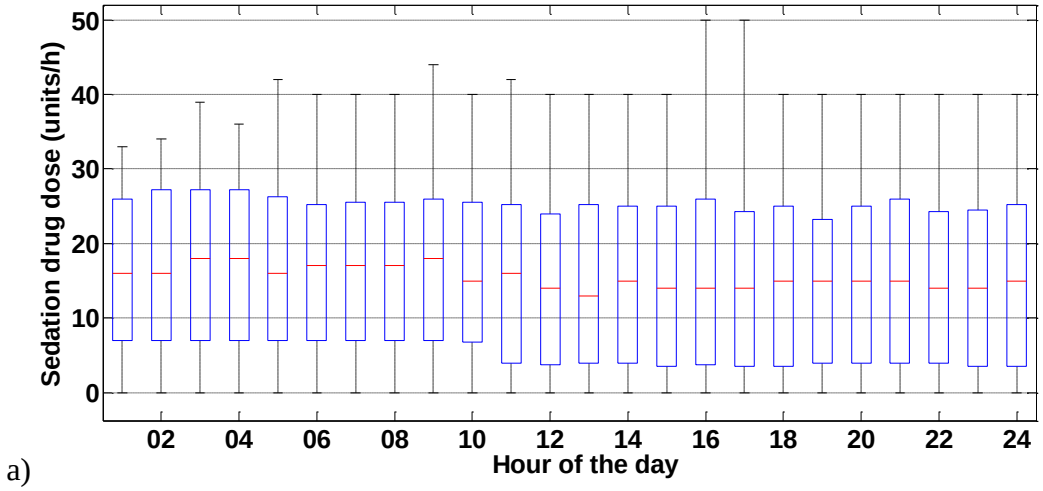


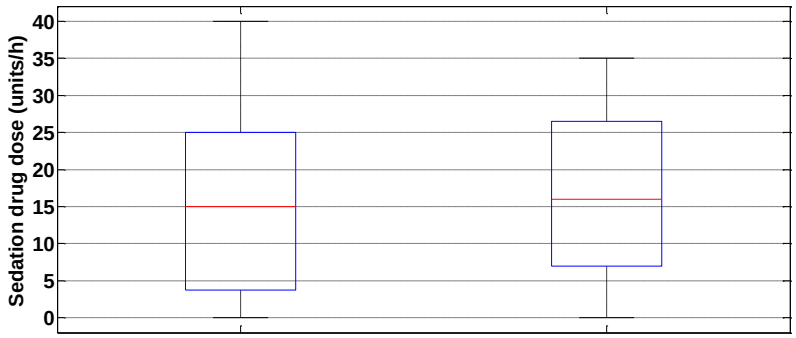
Figure 8.7: (a): 24-hour RASS distribution for Patient Group C; (b): Day (7am - 11pm) and night (11pm - 7am) RASS distribution.

8.4.2 Sedation drug dose distribution

Figure 8.8 shows the patient 24-hour average sedative drug dose distribution for Patient Group B. It also shows daytime (7am - 11pm) and night time (11pm - 7am) average sedative drug administration. Drug dose level is slightly higher during the night (median = 16 units/hour) than day (median = 15 units/hour), but with no statistical difference (p=0.19, using Ranksum test).



a)



b)

Figure 8.8: (a): 24-hour sedative drug dose distribution for Patient Group B; (b): Day (7am - 11pm) and night (11pm - 7am) sedative drug dose distribution.

8.4.3 Correlation between day dose and night dose

Figure 8.9 shows the Pearson correlation between sedative drug usage during the day and the night (R=0.81) for Patient Group B. The line slope <1 shows that the drug dose during the night is slightly higher than during the day. However, nightly drug dose is quite variable by patient and patient day.

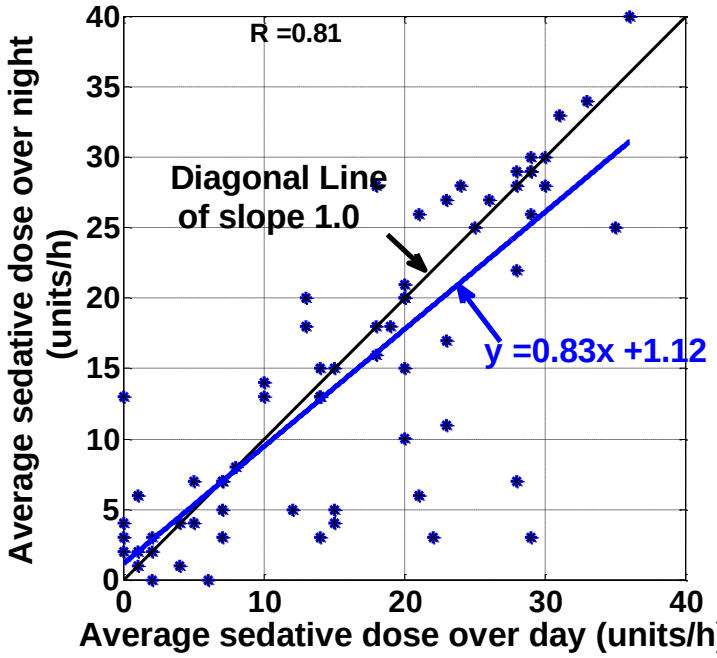


Figure 8.9: Daily and nightly sedative drug dose are highly correlated.

Figure 8.10 shows the hourly cumulative distribution of patient drug dose during the day, night, and entire 24-hour period respectively for Patient Group B. Night doses tend to be higher for those given less than the median 14-15 units/hour and the curves have clinically or statistically difference ($p = 0.0018$ using K-S test2). Table 8.2 shows the 5^{th}, 25^{th}, 50^{th}, 75^{th}, and 95^{th} percentile of 'day', 'night', and '24-hour' drug dose.

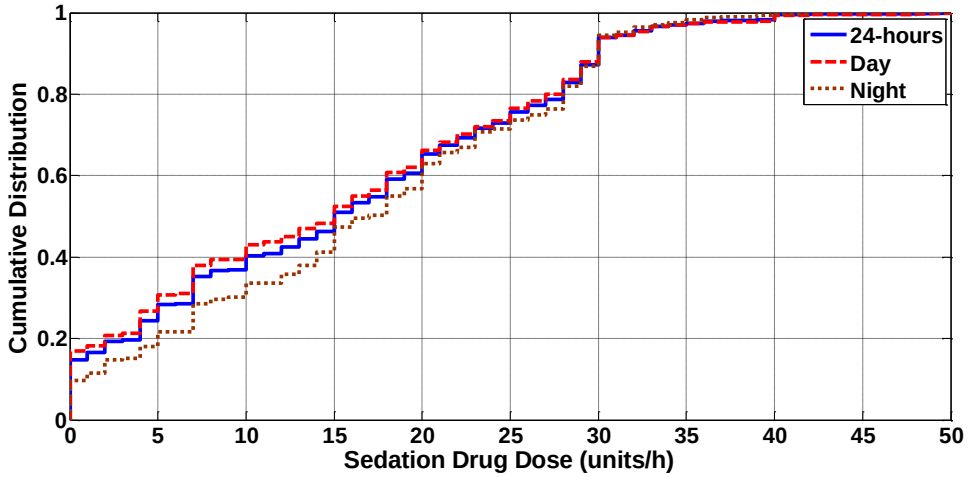


Figure 8.10: Cumulative distribution of sedative drug dose during day and night in Patient Group B.

Table 8.2: 5^{th}, 25^{th}, 50^{th}, 75^{th}, and 95^{th} percentile of average dose for the day, night, and entire 24-hour period (units/hour)

Percentile	**5^{th}**	**25^{th}**	**50^{th}**	**75^{th}**	**95^{th}**
Day	0	4	15	25	32
Night	0	7	17	27	31
24-hour	0	5	15	25	32

Results shown in Figures 8.7 - 8.10 and Table 8.2 suggest that patients in Patient Group B received slightly more sedation at night than in the daytime. Sedative drug dosage should be patient-specific and depend on patient-specific condition. Thus, results here may suggest that patient illness during the night requires higher dosage than during the daytime. Alternatively, it could be a clinical practice, whether by intention or unintended, that more sedative drugs were given at night.

8.5 Nursing workload and patient sedation level

8.5.1 Nursing workload and RASS

Figure 8.11 shows the nursing time distribution as a function of RASS scores for Patient Group A, where nursing time was measured using CATS. Patients receive significantly more nursing care minutes when patient RASS scores = 0 or -5 ($p<0.05$). No significant difference was found for other groups ($p>0.05$). Figure 8.12 shows the correlation between average RASS of each day and corresponding nursing time, with no clear correlation ($R = 0.07$). The results show RASS score and nursing effort are effectively unrelated with no clinically explainable trend.

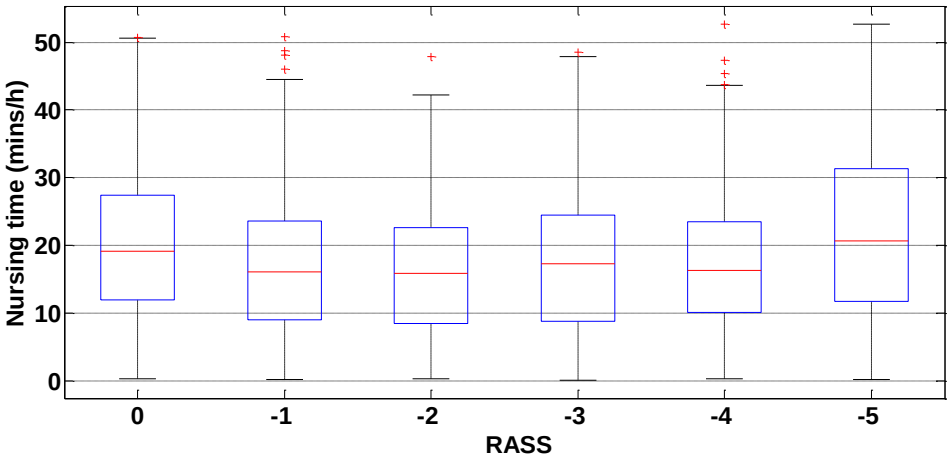


Figure 8.11: Nursing time distribution based on different RASS scores for Patient Group A. Four hours of +1 data is combined with RASS = 0.

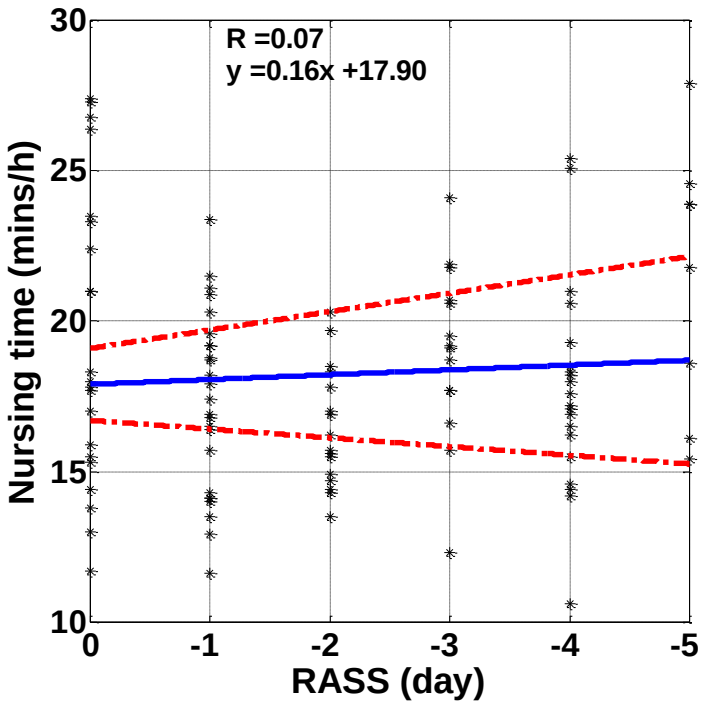


Figure 8.12: Correlation between nursing time and RASS scores for Patient Group A.

8.5.2 Correlation between nursing workload and GCS

Figure 8.13 shows the nursing time distribution as a function of GCS for Patient Group A. Figure 8.14 shows the correlation with R=-0.10. As with RASS score there is no correlation or clinically explainable trend. The low to zero slope in Figure 8.12 and 8.14 show no difference in nursing time as a function of sedation level.

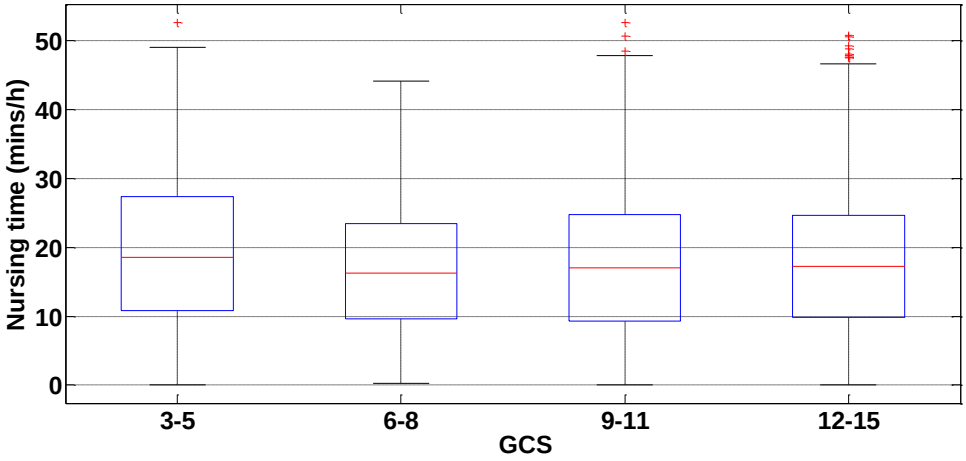


Figure 8.13: Nursing time distribution based on different GCS scores for Patient Group A.

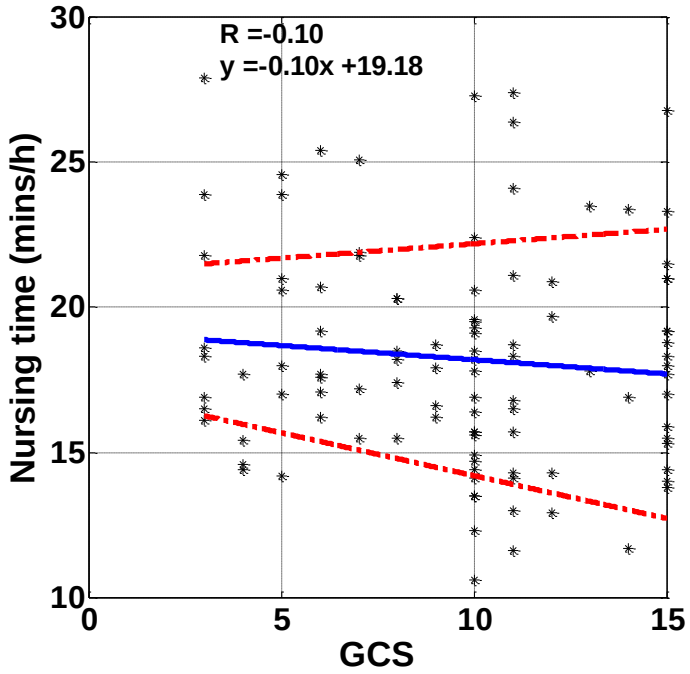


Figure 8.14: Correlation between nursing time and GCS scores for Patient Group A.

8.5.3 Correlation between nursing workload and sedative drug dose

Figure 8.15 shows nursing time distribution, as measured by CATS, for different sedative drug dosage for Patient Group A (all 23 patients). Results show no significant trend that is clinically explainable across dosing levels. The only possible exception is where the highest sedation doses required 2-3 minutes (at median) less nursing time per hour ($p<0.05$) than other sedation doses. It is possible that the patients who received the highest sedation have

slightly lower nursing workload due to less direct communication between nurse and patient.

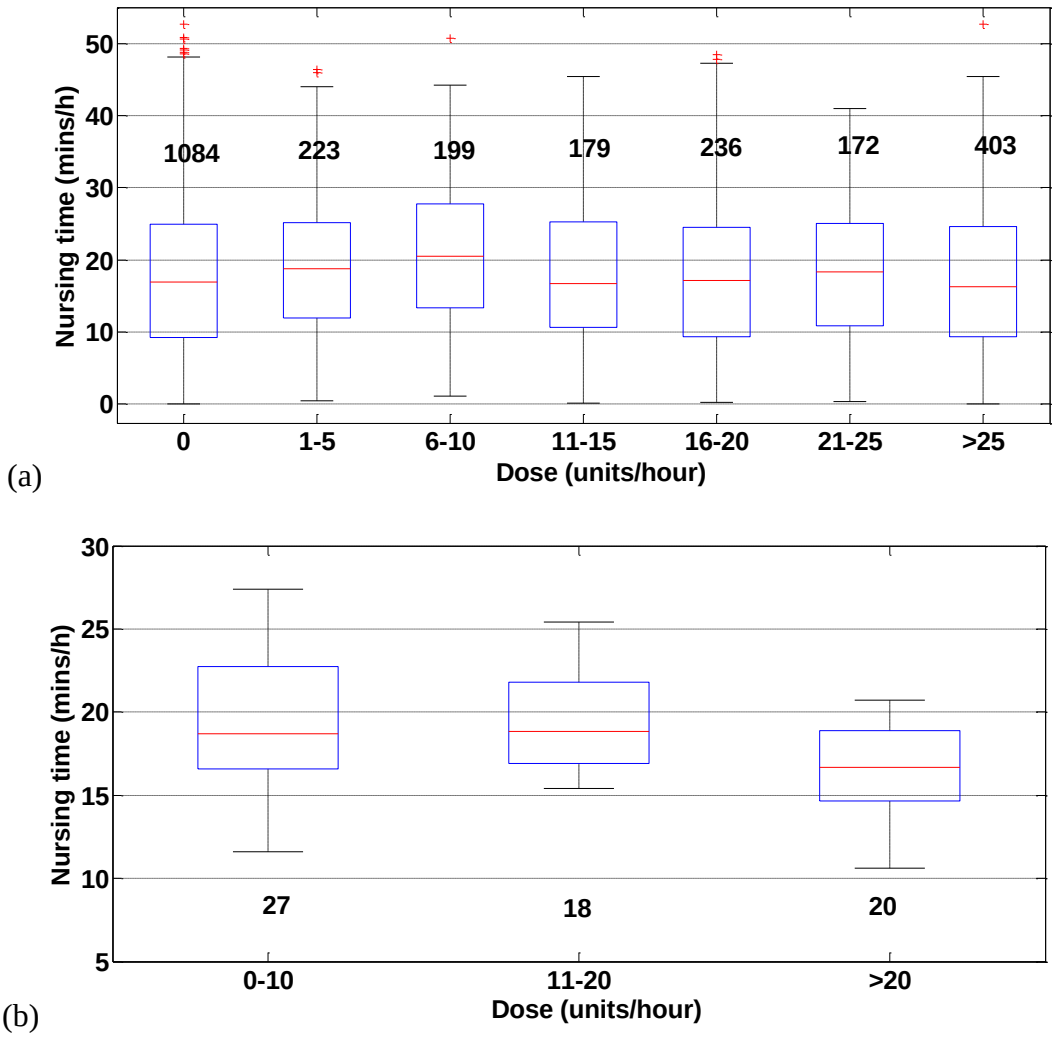


Figure 8.15: Nursing time distribution based on different sedative drug dose. (a): Data from Patient Group A. Number of patient hours is presented on each box. (b): Data based on 65 patient days from Patient Group D). Number of patient days is given below each box.

Figure 8.16 shows the correlation plot (R=-0.29) using only those patient receiving sedation (Patient Group D). It suggests nursing time drops as sedative dose rises. However, the variability is so large that the trend is not clinically useful.

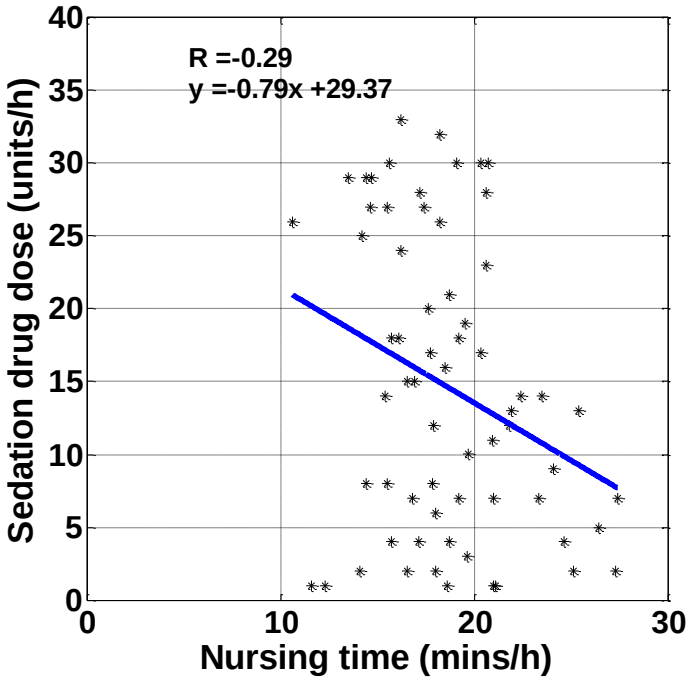


Figure 8.16: Correlation between nursing time and sedative drug dose, based on 65 patient days, only includes patient with LOS more than 3 days and patient requires sedative drugs.

8.6 Summary

In this chapter, it analysed patient sedative level by RASS, GSC and sedative drug dose. Patient sedation level is compared with nursing time. The clinical expectation is that patients require less nursing effort when they are more sedated. Results show that this clinical expectation exists in general but, patient-specific results are highly variable. No clinically significant trend is found in nursing time, sedative dose, or sedation level, as assessed by GCS or RASS.

In the next chapter, nursing intervention time is compared with other factors that could influence workload level, such as patient age, acuity level, day or night. This study will further improve the understanding of the factors influencing observed changes in nursing workload, given that sedation level and dosing are not a factor.

Chapter 9 Relation between CATS nursing intervention and patient clinical conditions

Chapter 7 presents the clinical patient acuity scores, where a moderate correlation was found between TISS-28 assessed nursing workload and patient acuity level. However, TISS-28 has poor resolution and was thus not able to capture actual nursing workload. Chapter 8 found no correlation between sedation level and acuity or workload, eliminating a major factor believed to influence workload. In this chapter, patient-specific nursing workload time, quantified using CATS, is compared with other patient-specific clinical information to evaluate which clinical factors could possibly have a stronger influence on nursing workload.

9.1 Introduction

Nursing workload is patient-specific and hard to quantify, and is affected by a range of factors [296]. In the literature, several possible factors are listed:

1. *Time of the day.* Nursing work shifts are normally divided into either three 8-hour shifts, 'Morning, Evening, and Night', or two 12-hour shifts, 'Day' and 'Night'. Miranda et al. [2] showed that category 1 and 2 nursing activities account for 55%, 63%, and 50% of the entire nursing time during Morning, Evening, and Night shifts, respectively. Category 1 and category 2 nursing activities are activities directly related to the patient, such as ventilator support, renal support, neurologic support, communication with the patient, comforting, hygiene, lifting, and safety. This suggests that nurses are most busy during the evening and least busy during the night.

Most of nursing interventions CATS captures are direct, category 1 and 2, nursing activities, accounting for 55-63% of nursing time. Gerasimou-Angelidi et al. [104] noted that NAS values revealed a shortage of nurses during morning shifts. Debergh et al. [297] showed that NAS was influenced by the patient characteristics and the type of shift, where NAS scores were lower during night shifts and weekends. Interestingly, these results coincide with the findings in Chapter 6, where nursing interventions during day and night can vary dramatically, showing the importance of quantifying nursing workload by time of day.

2. *Patient illness severity.* As discussed in Chapter 7, many different assessment tools can be used to evaluate patient illness severity, such as APACHE, SAPS, and SOFA. Many studies have stated that patient illness severity can affect nursing workload. Padilha et al. [103] found that very high SAPS-II scores (>46.5) increased the probability of high NAS by 2.78 times. Mion et al. [226], and Kiekkas et al. [229] noted that clinical severity values on patient admission are important predictors of daily nursing workload. Castillo-Lorente et al. [225] found that both APACHE-II and APACHE-III have significant positive correlation with both TISS-28 and TISS-76. Finally, Kwok et al. [227] found good correlation between TISS-28 and SAPS-2.

However, several other studies found opposite results, stating that patient degree of illness did not necessarily reflect the demand for nursing care. Oye et al. [232] stated that patients with the highest TISS-76 scores were found to have intermediate APACHE-II scores. Weak correlation between NAS and SAPS-II was found (r=0.24) by in Lucchini et al. [263]. Edwardson et al. [230] stated that clinical severity scores reflect patient dependency, rather than nursing dependency and effort. Endacott et al.

[231] showed that clinical severity scores do not necessarily encompass the complexity of nursing activities, which means that the amount of nursing work does not directly correspond with an individual patient's level of care.

The variability in results relating patient clinical severity and nursing workload show it is necessary to further investigate this issue. CATS provides an objective resource for monitoring direct nursing activities. Therefore, it can provide a unique insight that all these prior studies cannot.

3. *TISS and NEMS.* Existing nursing workload assessment tools, such as TISS-28 and NEMS may not be able to fully assess nursing workload. Castillo-Lorente et al. [216] stated that TISS-28 scores in their study could only account for 32% of a patient's average nursing intensity during the period of treatment. Miranda et al. [78] further showed that TISS-28 was only able to account for around 42% of the ICU nursing workload. These studies coincide with the results presented in Chapter 7, where TISS-28 was not sensitive or precise enough to differentiate variability between patient-specific care based on illness. It is necessary to further investigate whether TISS-28 or NEMS can capture nursing workload in the ICU. More specifically, this study will be carried out using data from the Christchurch Hospital ICU.

4. *Patient age and gender.* Both patient age and gender may influence the intensity of the nursing workload [298, 299]. Lucchini et al. [263] found that the differences amongst the various age groups were not statistically significant, except for patients with age <10 years. Lundgrén-Laine et al. [216] found only a weak statistical correlation between nursing intensity and patient age, as well as gender. However,

Castillo-Lorente et al. [300] showed that age is an important factor influence the workload. Interestingly, they stated that patients with age > 75 years required lower levels of care, as well as those with lower TISS score. In particular, they reported a negative correlation between the age of ICU patients and TISS-76, which resulted from the fact that therapeutic activity was significantly lower for patients aged >75 years. However, no differences in therapeutic activity existed among the other age groups (<75 years) [300]. In addition, considering the fact that male and female patients in the ICU have different mortality risks, different LOS [301, 302], and different personality, patient gender could possibly affect nursing workload. Thus, it is necessary to further investigate whether patient age and gender have correlation with nursing workload in this study, using an objective measure of direct nursing activity.

5. *Patient length of stay (LOS).* LOS may also affect nursing workload. Some studies suggested that a lower LOS resulted in increased nursing care [303]. A weak positive correlation was observed between LOS and nursing workload by Lundgrén-Laine et al. [216]. However, other studies suggest the different results [29, 304-306]. Gonçalves et al. [298] found a significant correlation between patient LOS and nursing workload, with a progressive increase in average nursing workload as LOS rose. Lucchini et al. [263] reported that an increase in patient LOS resulted in an increase of the median daily NAS for each group investigated. And some studies even suggest that non-surviving patients require higher nursing workload [307, 308]. Thus, these varied and sometimes contradictive results mean there is a need to study the effect of LOS on nursing workload, using an objective measure provided by CATS.

6. *Patient diagnosis and type of ICU.* Nursing requirements can also vary in different types of ICU. Lucchini el al. [263] reported that the median NAS of patients admitted to the GICU (General ICU) was higher than patients in the Neuro ICU and Cardio ICU. Their research also showed that different patient illness/condition types have different median NAS score. Debergh et al. [297] showed that patient NAS scores were lower in Medical ICU (MICU). Sessler et al. [281] stated that different types of ICU would influence the required nursing workload. All these studies stated that different patient and ICU types can affect nursing workload.

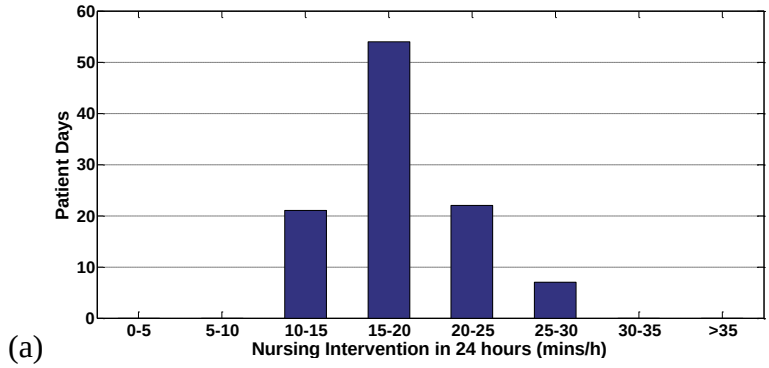
7. *Other factors.* Based on ICU specialist experience, other factors which could possibly affect nursing workload in clinical practice include mechanical ventilation management, decision around patient FiO2 levels, patient intubation condition, patient admission type, and patient chronic disease history.

9.2 Correlation between nursing workload and different time of the day

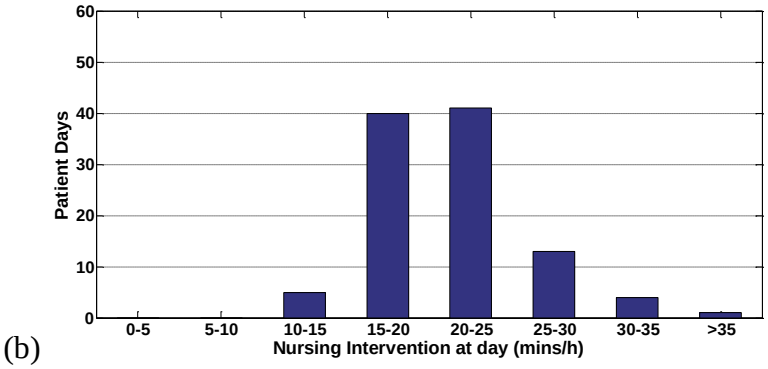
Figure 9.1 shows the distribution of average direct nursing intervention. Day time defined in this study is 7am to 11pm (16 hours), whereas night time is 11pm to 7am (8 hours). For the 23 patients and 104 patient days included in this study, 53 days (51%) had an average nursing intervention time between 15 to 20 min/hour. For the 24-hour period, more than half of patient days have an average nursing intervention time of 15-20 min/hour. When separated by day and night, 81% of total days have 15-25 minutes of nursing intervention during day time, and this majority shifts during the night time for a significantly lower ($p<0.05$) nursing intervention time of 5-15 min/ hour.

Figure 9.2 shows the cumulative distribution of nursing intervention time during the day,

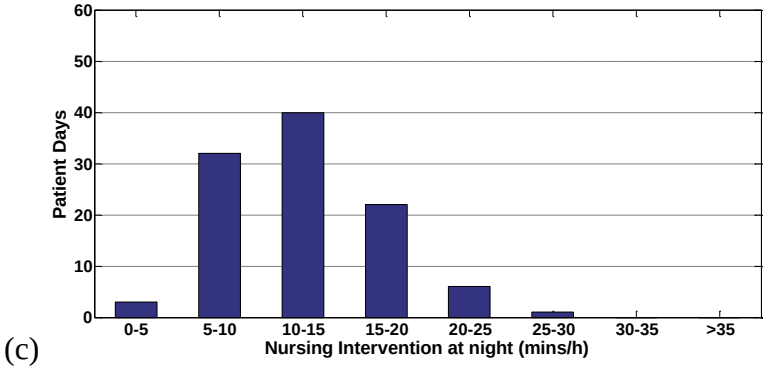
night, and 14-hour periods, and Table 9.1 shows the 5th, 25th, 50th, 75th and 95th percentile of the hourly nursing intervention for each of these periods. Results clearly show that the daytime hourly nursing intervention time is higher than at night, and more direct nursing activity work is performed during daytime ($p<0.05$).



(a)



(b)



(c)

Figure 9.1: (a-c): The distribution for average nursing intervention time per day, 24-hour, day time, and night time. (a) is not simply the average of (b) and (c) as high day-time intervention caused 24-hour intervention much higher than night-time intervention.

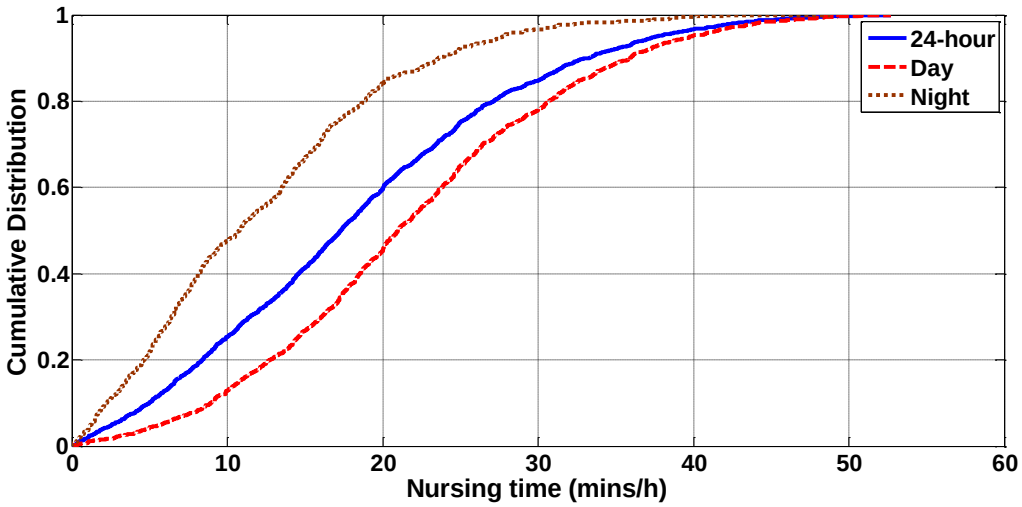


Figure 9.2: Cumulative distribution of nursing intervention.

Table 9.1: 5% CI, 25% CI, median, 75% CI, and 95% CI of nursing intervention time (minutes/hour) during the day, night, and 24-hour period

Percentile	5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
Day	5.75	14.5	21	28.5	39.8
Night	1.29	5.6	10.75	17	27.71
24-hour	2.6	9.9	17.3	25	37.6

Figure 9.3 shows the moderate correlation (R=0.39) between average nursing intervention time per hour over the night and day periods. The hourly nursing intervention conversion between night and day time is:

$$C_{K13}\,(\text{day}) = 0.37 \times C_{K13}\,(\text{night}) + 16.68 \qquad (9.1)$$

where C_{K13} represents CATS captured direct nursing intervention activity time in the K13 area.

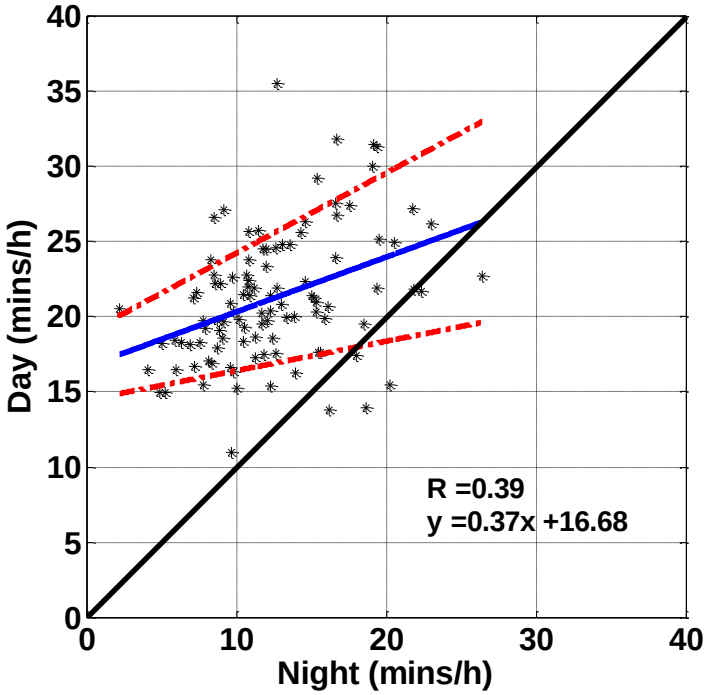


Figure 9.3: Correlation between average nursing intervention time at night and day. X-axis represents the average nursing intervention of each night (11 pm – 7 am); Y-axis represents the corresponding nursing intervention of each day (7 am – 11 pm).

Patient nursing demand is clearly higher during day time, where many direct nursing activities only occur during the day, such as preparing meals, dressing patients, and communicating with patients and families. In contrast, patients were 'less interrupted' during night time. Based on observations, the nurses' main role during night shift appears to be ensuring patients have adequate rest, rather than giving or adjusting treatments. Comparatively, during day time, nurses perform all routine checks, and in addition, more organisation and coordinating tasks with doctors, family members, and administration works were also observed. All these tasks increase the overall nursing workload during day time.

9.3 Correlation between patient acuity level and nursing workload

9.3.1 Correlation between patient APACHE-II scores and nursing time

Figure 9.4 shows the correlations (R = 0.10 - 0.26) between APACHE-II and nursing time during day, night and 24-hour period, for all patients. Weak correlations show only limited

change of effort with patient acuity measured by APACHE-II. The correlation is highest during night time (R = 0.26), which could be due to the fact that the limited nursing interventions performed at night may be much more directed towards a patient's level of illness than during the day time, which has much more routine work common to all patients.

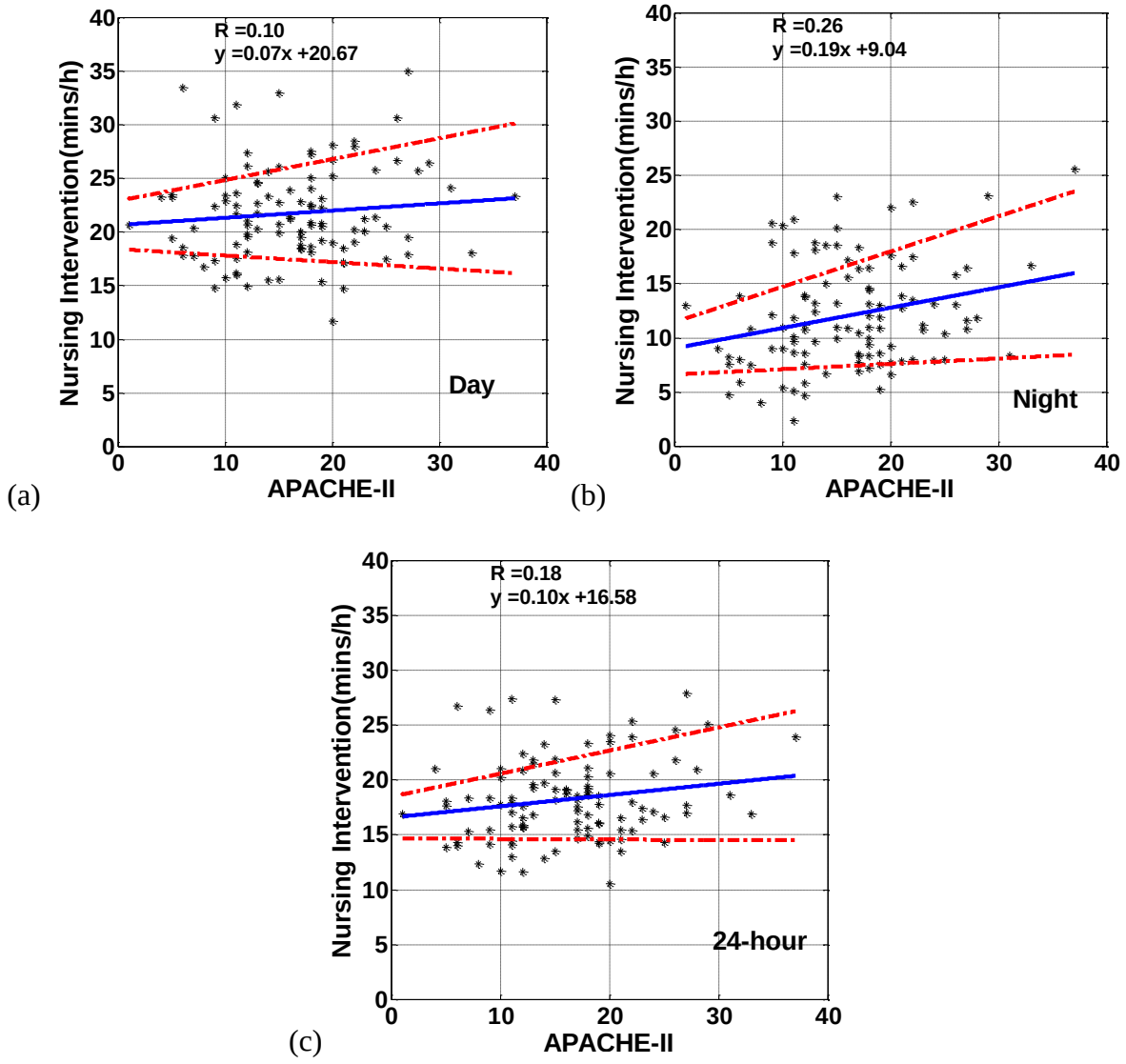


Figure 9.4: (a-c): Correlation between patient APACHE-II scores and CATS recorded nursing time during day, night, and 24-hour, respectively.

9.3.2 Correlation between patient APACHE-III scores and nursing time

APACHE-III consists of several important evaluating scores, such as patient sedation, age, comorbidity scores and patient physiology severity scores. In this section, only the

relationship between APACHE-III and APACHE-III physiology severity scores, and nursing intervention are presented. This latter score ranges from 0-204, where the sedation score (48), age score (24) and comorbidity scores (23), are subtracted from the total APACHE-III score of 299. Figure 9.5 shows the correlations for each score and nursing time.

Figure 9.5 shows weak positive correlations (R=0.10-0.32) and wide 95% CIs for all correlations between APACHE scores and nursing intervention time over the day, night, and entire 24-hour period. These results suggest an increase in severity of patient condition will have only a modest influence on nursing workload, similar to the APACHE-II results in Figure 9.4.

9.3.3 Correlation between patient SAPS-II scores and nursing time

Figure 9.6 shows similarly weak (R=0.11-0.26) correlation between SAPS-II and nursing time. Similar to the APACHE-III physiological scores, Figure 9.6 shows the patient requires only slightly more nursing care when patient acuity level rises, if any. Again, the night period had the highest correlation.

9.3.4 Correlation between patient SOFA scores and nursing time

Figure 9.7 shows correlations (R=0.13-0.28) between SOFA score and nursing time, with the strongest at night. This result further confirms similar findings in APACHE scores or SAPS, where night time nursing interventions are more directed towards severity of the illness than during the day, where the correlation has a slope of 0.0 indicating no influence at all from severity measured by SOFA.

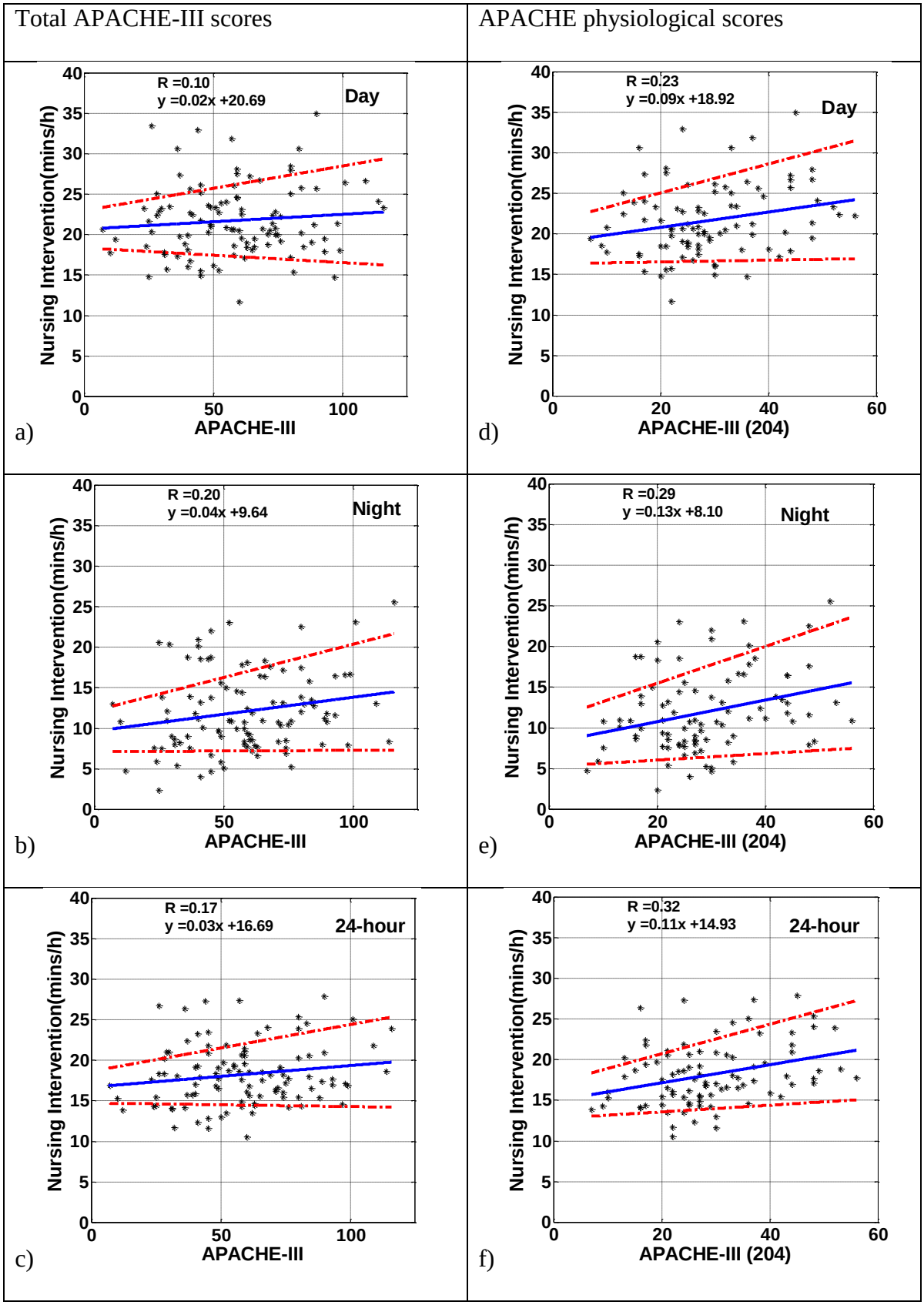


Figure 9.5: (a-c): Correlation between patient APACHE-III scores and nursing time during day, night, and entire 24-hour period, based on 104 patient days. (d-f): Correlation between patient APACHE-III (204) and nursing time during day, night, and entire 24-hour period.

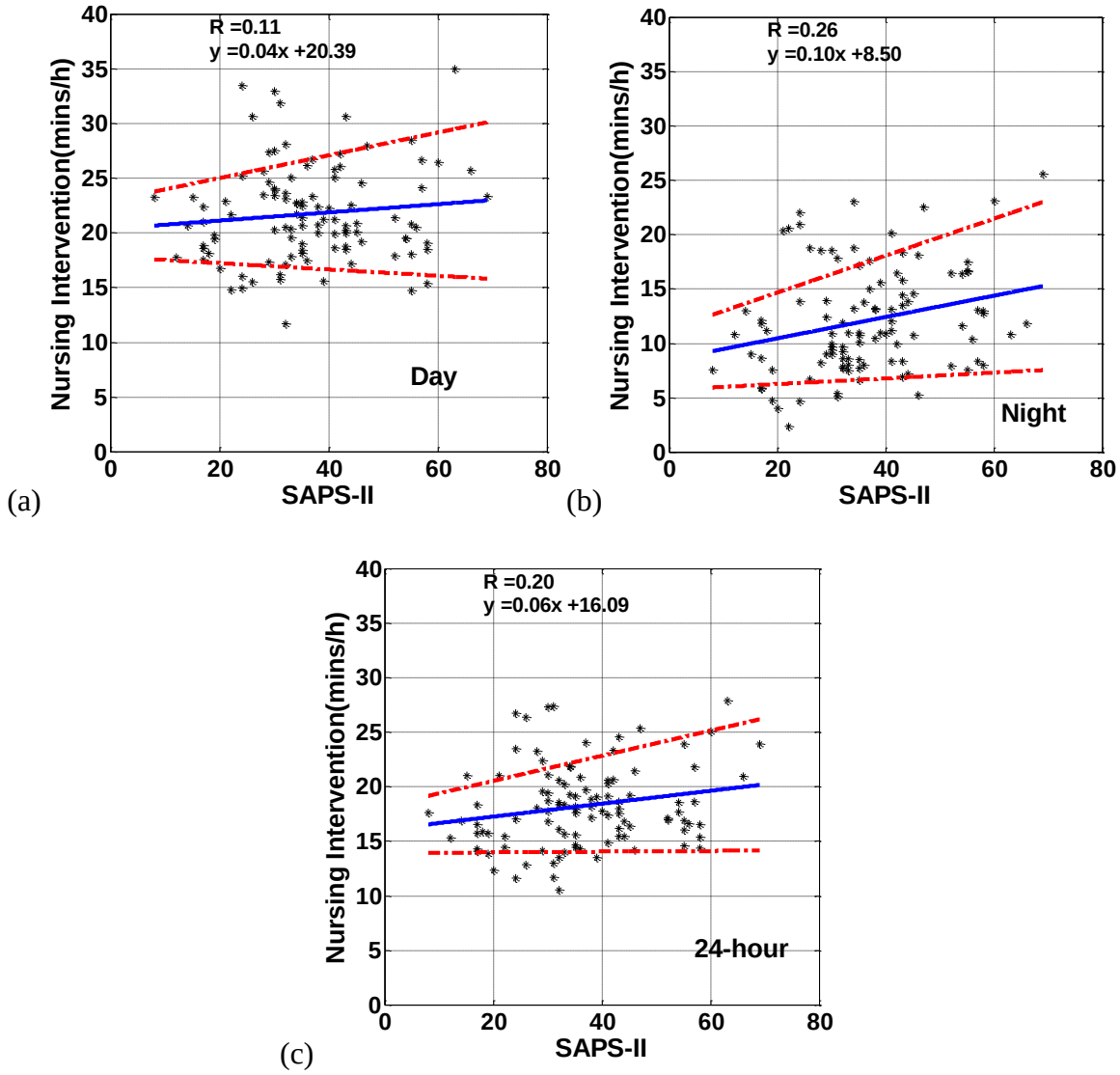


Figure 9.6: (a-c): Correlation between patient SAPS-II scores and average nursing time during day, night, and entire 24-hour period, based on 104 patient days.

9.3.5 Correlation between patient TISS-28 scores, NEMS and nursing time

Figure 9.8 shows very weak correlation (R=0.04-0.17) between TISS-28, NEMS, and CATS assessed nursing time. The 95% CI bands are also extremely wide, spanning almost any possibility. The results also show the lack of resolution of both TISS-28 and NEMS scores to assess direct nursing effort, where both scores exist over very narrow score ranges, further lowering the correlation value.

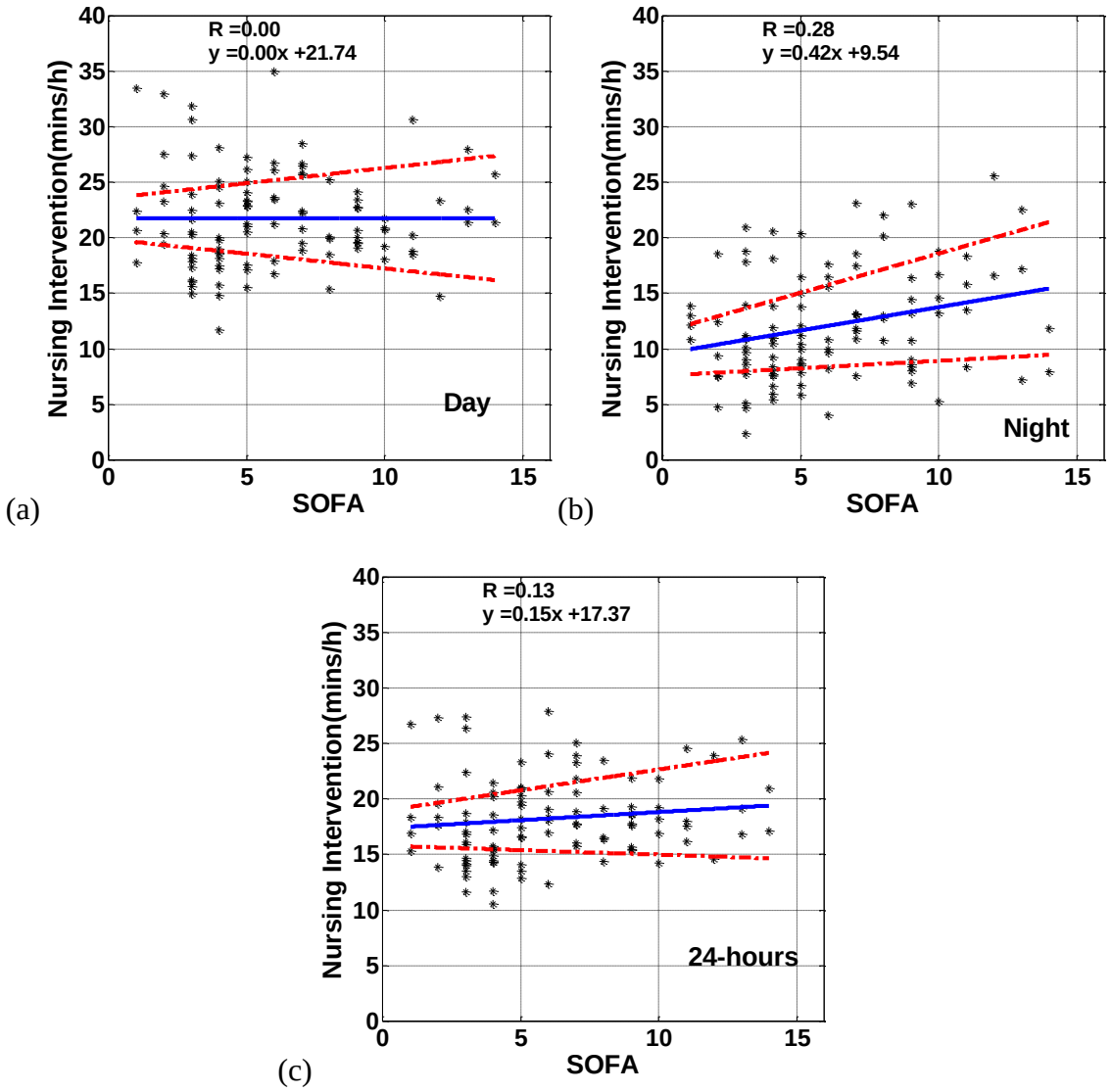


Figure 9.7: (a-c): Correlation between patient SOFA scores and average nursing time during day, night, and entire 24-hour period, based on 104 patient days.

There is almost no relation between the CATS calculated nursing intervention and TISS-28 or NEMS. Thus, in this study, it was found that neither of these scores can represent the actual, directly measured and objective clinical workload, confirming the need for an objective method to measure bedside clinical activities, which this study has provided.

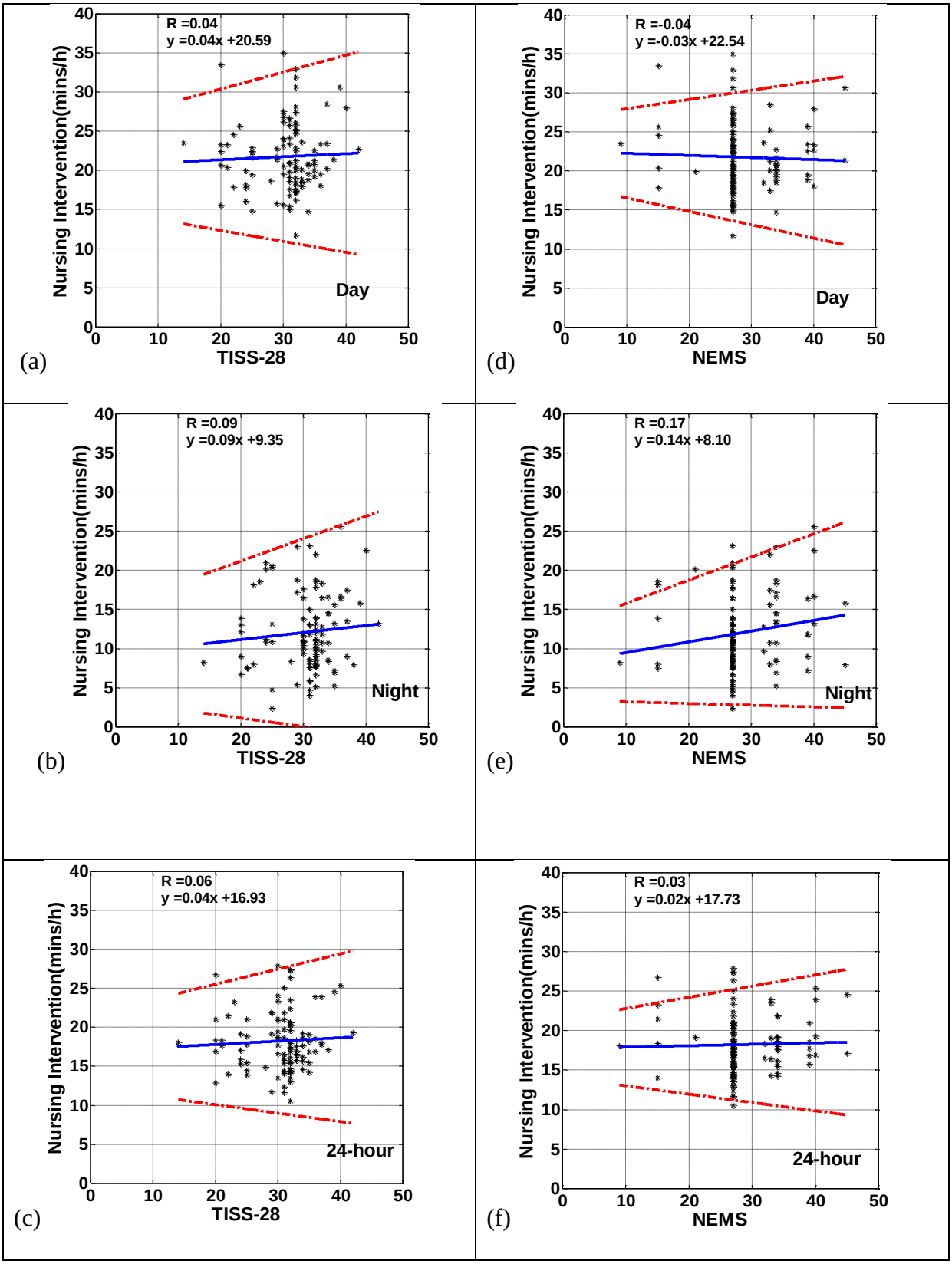


Figure 9.8: (a-c): Correlation between patient TISS-28 scores and average nursing time during day, night, and entire 24-hour period, based on 104 patient days. (d-f): Correlation between NEMS scores and average nursing time during day, night, and entire 24-hour period.

9.4 The influence of other factors to nursing time

9.4.1 Correlation between patient age and nursing time

APACHE-III divides patient age into 7 groups. In this research, the patients are divided into 4 age groups considering the patient cohort. This research combines groups 60-64 and 65-69 into 60-69, groups 70-74 and 75-84 into 70-84, and eliminates group ≥ 85 as there were no patients in this cohort. Thus, the patients are separated into 4 age groups: 18-44, 45-59, 60-69, and 70-84.

Figure 9.9 shows 24-hour nursing time for each age group. Patient days are presented at the top of each box. None of the age groups showed a statistically significant difference ($p>0.09$). Figure 9.9 also shows weak correlation ($R=0.14$) between patient age and 24-hour nursing time. In addition, only a moderate correlation ($R=0.32$) is found between patient age and 'patient average' nursing time over their whole stay, for all 23 patients.

9.4.2 Correlation between patient gender and nursing time

There are 23 patients admitted during this research, of which 13 were male. Figure 9.10 shows nursing time distribution based on patient gender based on 24-hour average (a) and per-patient (b). Males make up 70/104=67.3% of patient days and 13/23=56.5% of patients. Male patients require more nursing care than female patients, ignoring illness severity, with median nursing time for male and female patients at 18 and 16 minutes/hour respectively ($p=0.03$). The difference per-patient shows greater variability across female in Figure 9.10(b).

9.4.3 Correlation between admission type and nursing time

For the participating cohort, there are 3 different patient admission types: 1) Scheduled (elective) surgical; 2) Medical; 3) Unscheduled (Emergency) surgical. In this research, one

patient (2 patient days) was ‘Scheduled surgical’; 18 patients (85 patient days) were ‘Medical’; and 4 patients (17 patient days) were ‘Unscheduled surgical. Figure 9.11 shows no significant difference in nursing time distribution based on different admission types by patient day (a) or per-patient (b) (p>0.55).

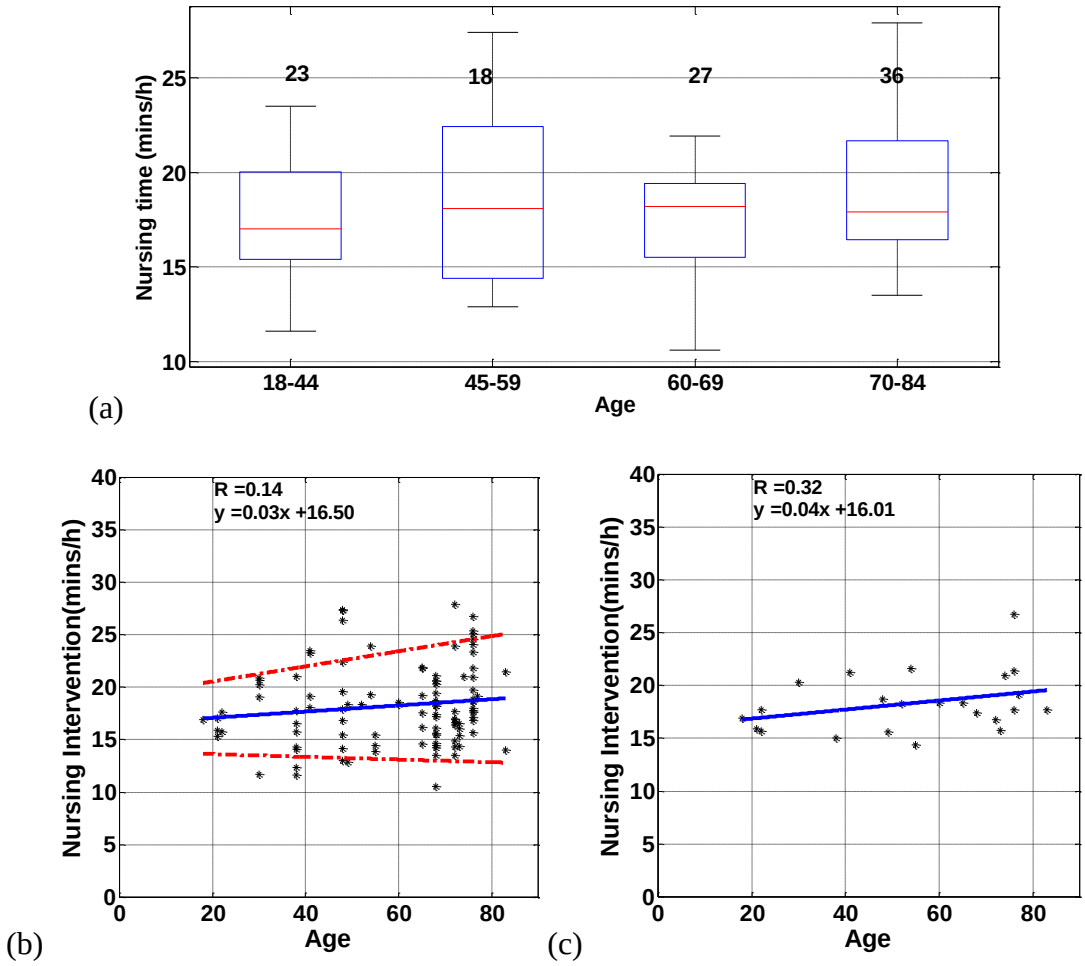


Figure 9.9: (a): Nursing time distribution according to different age groups. Patient days are presented at top of each box. (b): Correlation between patient age and ‘day average’ nursing time, based on 104 patient days. (c): Correlation between patient age and ‘patient average’ nursing time, based on 23 patients. Day average nursing time is the average nursing time during every 24 hours, while patient average nursing time is the average nursing time during every patient’s LOS.

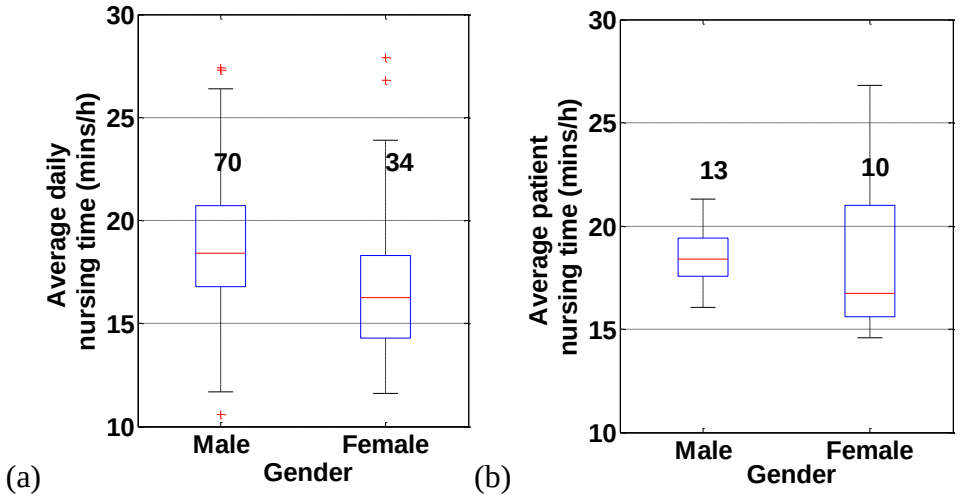


Figure 9.10: Nursing time distribution based on different patient genders. (a) is based on 104 patient days, of which 70 days were from male patients; (b) is based on 23 patients, of which 13 are male patients.

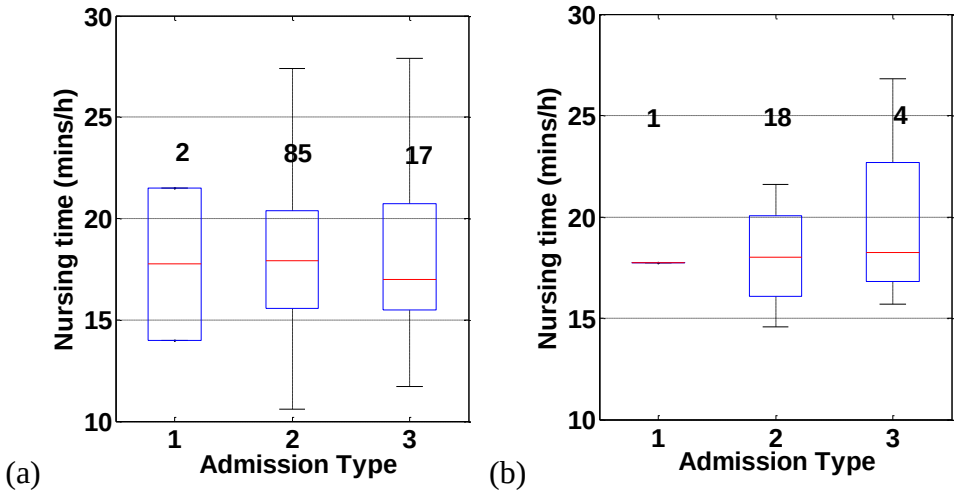


Figure 9.11: Nursing time distribution based on different admission types. (a) is based on 104 patient days, and total patient days are presented at the top of each box; (b) is based on 23 patients, that number of patients are presented at the top of each box. Patient admission types include: 1) Scheduled (elective) surgical; 2) Medical; 3) Unscheduled (Emergency) surgical.

9.4.4 Correlation between patient intubation condition and nursing time

Patients are also divided into an 'Intubation' group where patients require invasive mechanical ventilation, and a 'Non-Intubation' group. Figure 9.12 shows no significant difference in nursing time distribution by patient intubation condition ($p>0.40$) per-day or per-patient.

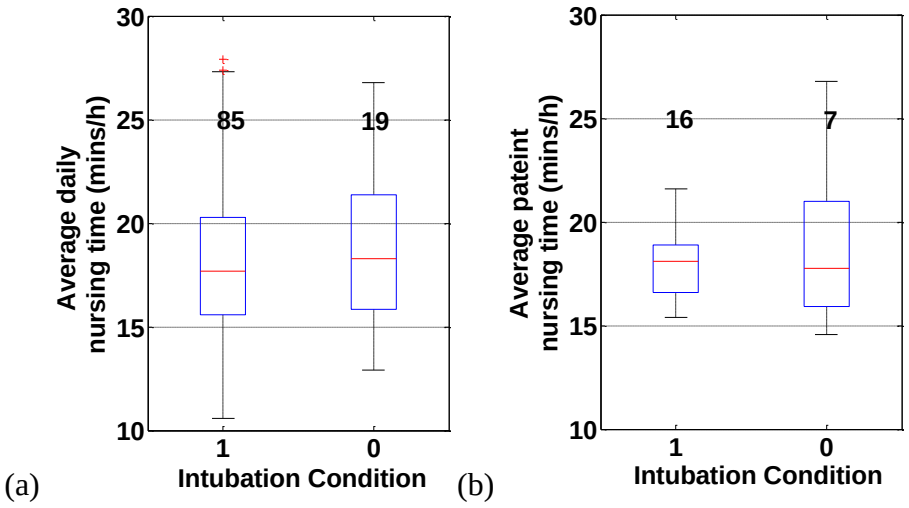
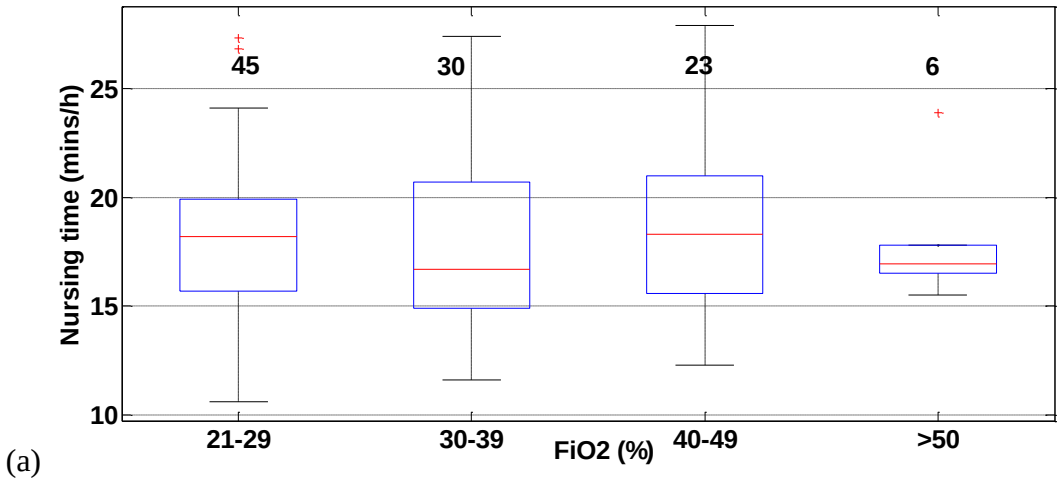


Figure 9.12: Nursing time distribution based on patient's different intubation conditions. (a) is based on 104 patient days, where total patient days for each group are presented at the top of each box; (b) is based on 23 patients, and the number of patients in each group are presented at the top of each box. Intubation Condition: '1' represents Intubation; '0' represents Non-Intubation.

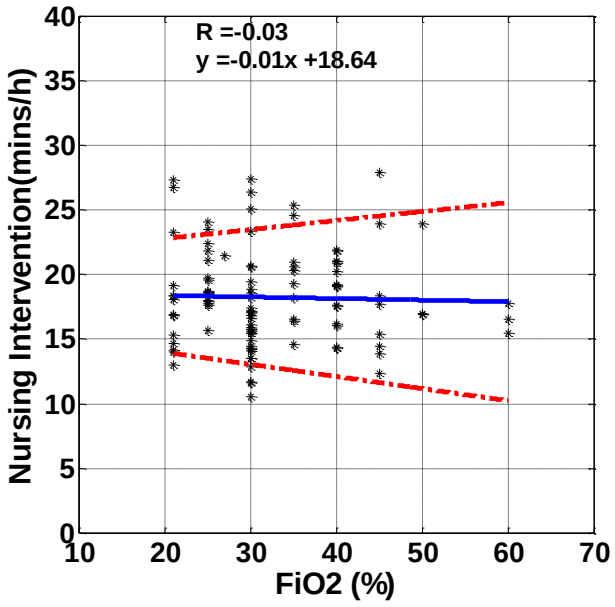
9.4.5 Correlation between patient FiO_2 level and nursing time

For patients requiring mechanical ventilation, the Fraction of Inspired Oxygen (FiO_2) varies from patient to patient, ranging from 21%-100%. Patients requiring higher FiO2 may be associated with more severe forms of respiratory disease and require higher support [309, 310]. Thus, it is an indirect measure of the patient's acuity level.

In this study, 21 of 23 patients required mechanical ventilation support at some point and thus have patient and hour specific FiO2 settings. Figure 9.13 shows nursing time distribution based on different FiO_2. Figure 9.13 also shows the weak (R=-0.03) correlation between average nursing time each day and corresponding FiO_2 level. No statistically significant difference was found between nursing time and patient FiO_2 level ($p>0.48$).



(a)



(b)

Figure 9.13: (a): Nursing time distribution based on different FiO_2 range. Number of patient days is presented at the top of each box. (b): Correlation between nursing time and patient FiO_2 level, based on 104 patient days.

9.4.6 Correlation between patient LOS and nursing time

Patient LOS may affect nursing workload, as patients with long LOS tend to be more ill. Figure 9.14 shows nursing time based on patient length of stay (LOS). Results show nursing time was not different for different LOS ($p>0.55$). There is no significance difference in nursing time at different LOSs, even though longer LOS patients tend to have higher physiology scores, thus matching the results for APACHE-III in Section 9.3.2.

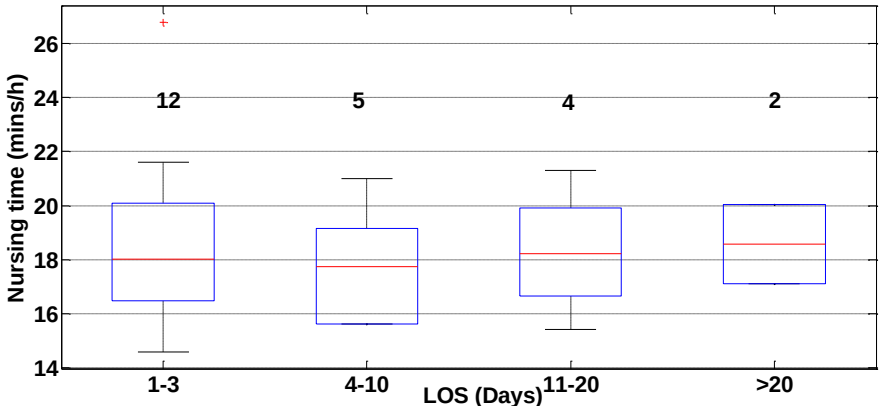


Figure 9.14: Nursing time distribution based on different LOS, for 23 patients. The number of patients is presented at the top of each box.

9.5 Summary

In this chapter, CATS captured nursing workload is compared with different possible factors could affect patient nursing demands. First, it shows that patient nursing demands are much higher during the daytime than during the night time. However, these extra demands appear to be largely due to more routine tasks not related to patient status or condition.

Second, comparing patient severity scores with CATS measured nursing work shows patient clinical severity has primarily only a weak correlation with objective measured nursing workload and acuity. This correlation is strongest at night when routine tasks are not typically performed, and thus nursing activity is more strongly related to patient dependence and thus severity.

Third, comparisons with TISS-28 and NEMS indicate that both TISS-28 and NEMS have poor resolution to assess nursing workload in the Christchurch hospital ICU. Equally, there was no link with other metrics, such as age, type of admission, intubation condition, FiO_2 level. Only ‘Gender’ was found to have statistically significant correlation with nursing time.

Chapter 10 Patient Specific Study and Recommended Nurse-To-Patient Ratio

10.1 Introduction

Chapter 9 analyzed possible factors affecting ICU nursing workload. It found that time of day and patient illness severity had only weak to moderate effects on nursing intervention time. Similarly, Chapter 8 found that patient sedation level had little to no effect on nursing workload. In this chapter, 6 of 23 patients are selected to further analyse the underlying causes of different per-patient nursing intervention times, taking into consideration different times of the day, patient acuity, patient sedation level, and patient diagnosis case by case. Results are compared to nurse-patient ratios calculated in the literature.

10.2 Patient specific study

To study which type of patient requires more nursing care, the 6 patients with LOS > 6 days were analysed in detail. Table 10.1 shows patient demographic and clinical details. Figure 10.1 shows the cumulative distribution (CDF) of hourly CATS nursing time in key detection areas K1 + K3 (Figure 5.1), over the day (7 am – 11 pm), night (11 pm – 7 am) and entire 24-hour period.

Table 10.1: 6 selected patients' demographics details, acuity evaluation levels, and nursing demands

	Patient Demographics Details				Acuity Evaluation			Sedation		Average Nursing Demands (minutes/hour) (Ranking)		
Patient Number	Age	Gender	LOS	APACHE III Diagnostic Code	APACHE-III	APACHE-III (204)	TISS-28	Dose	GCS	Day	Night	24-hour
4	72	F	70	1408.05 Gastrostomy	80	39	32	0	7	19 (1)	10.9 (3)	16.8 (2)
9	76	M	12	201.01 Respiratory Failure + Sepsis	87	40	32	2	6	26 (6)	13.3 (5)	21.4 (6)
11	65	M	23	602.11 Chest /thorax trauma	64	24	32	19	6	19.9 (3)	17.5 (6)	18.4 (4)
20	38	F	13	212.01 Pneumonia, bacterial	38	24	30	2	11	19.2 (2)	6.8 (1)	15.0 (1)
22	48	M	30	603.01 Burns	49	26	32	6	10	23.6 (5)	13.1 (4)	18.8 (5)
23	68	M	29	503.01 Sepsis with shock, not urinary	67	25	32	27	9	20.7 (4)	9.4 (2)	17.4 (3)

Note: These 6 patients stayed in Bed 7 for more than 6 days. Nursing demands are ranked from 1 to 6, that '1' means patient has the lightest nursing demands and '6' means the highest demands.

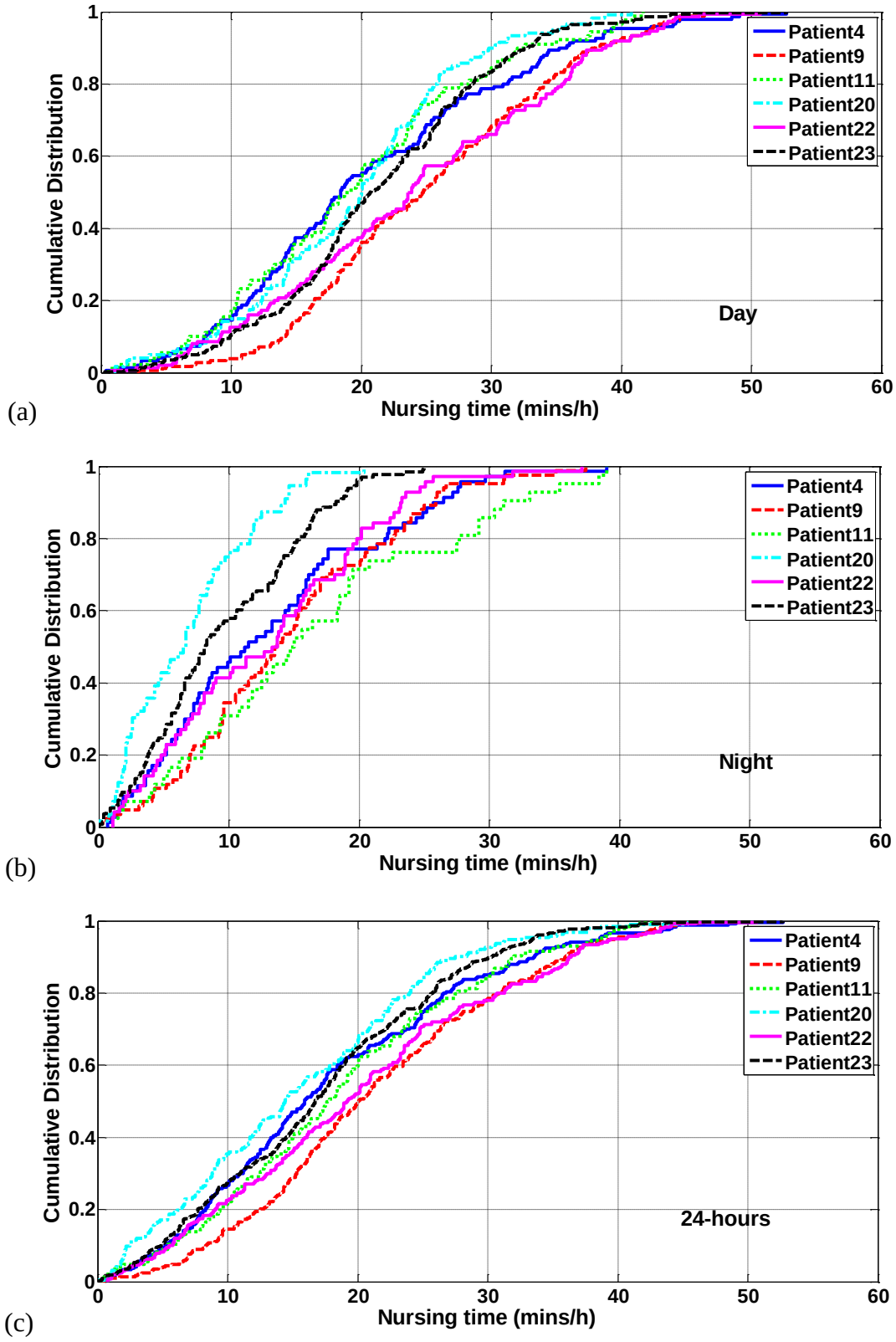


Figure 10.1: 6 patients (LOS>6 days) day, night, and 24-hour hour nursing time CDFs for each patient.

Of these 6 patients, Patient 20 requires the least average nursing time, and also has the lowest APACHE-III score. Patient 20 was diagnosed with pneumonia and required mechanical ventilation, which typically require greater sedation. Patient 20 had GCS = 10-11 for 8 days, with component values of eye = 3/4, verbal = 1/5, and Motor = 6/6, indicating they were neither dangerously sick nor requiring additional nursing input.

Patient 9 required the most nursing time and had the highest APACHE-III score and lowest GCS score. When compared with Patient 20, these results suggest that patient acuity and nursing time are associated, at least broadly. Patient 9 was diagnosed with respiratory failure and sepsis, where sepsis is a whole-body inflammatory response to an infection [311] associated with high mortality [312, 313]. Thus, diagnostically, this information suggests this patient is likely to require more attention and time.

Patients 11 and 23 have similar APACHE-III, but Patient 23 requires much less nursing care than Patient 11. In particular, during night time, Patient 23 shows over half of the nursing demands (53.7%) of Patient 11. Both patients received comparatively higher sedative drug dosage, with Patient 11 at 19 units/ hour and Patient 23 at 27 units/hour. For this subgroup analysis of 6 patients, Patient 23 received the highest sedative drug dosage. The use of high dose of sedative drug in Patient 23 may also help to explain the lower nursing workload during night time, as a highly sedated unresponsive patient may not have demanded additional attention. However, both patients were heavily sedated, so these cases show the lack of agreement to expected trends.

Patient 22 has a low APACHE-III score of 49, but received relatively high nursing time. This observation can be attributed to the primary diagnosis of ‘Burns’. It is likely that the patient

required far more routine nursing care, in number and intensity, than a typical ICU patient due to the additional demands and activities needed to treat burns.

Finally, Patient 4 had high APACHE-III score of 80, but required relatively low nursing time. This patient underwent a gastric surgical procedure and was in recovery. They thus likely required only routine nursing care, relative to other ICU patients.

For all 6 patients in this subgroup, nursing demands at night are significantly lower than in the day ($p<0.05$ by Ranksum test). Nursing care during night is also more variable, with a higher (median) range of 6.8 to 17.5 minutes/hour, compared to 19 to 26 minutes/hour over the day. As in Chapter 9, this difference may be credited to a more limited range of routine tasks being performed at night.

A total of 5 of the 6 patients had an average TISS-28 score of 32, and 1 patient a score of 30. This result clearly shows that the TISS-28 resolution is not high enough to differentiate patient-specific nursing demands. Thus, to assess nursing workload, it is necessary to consider patient acuity level, sedation level and type of diagnosis at a patient-specific level, as well as using a more direct, objective measurement.

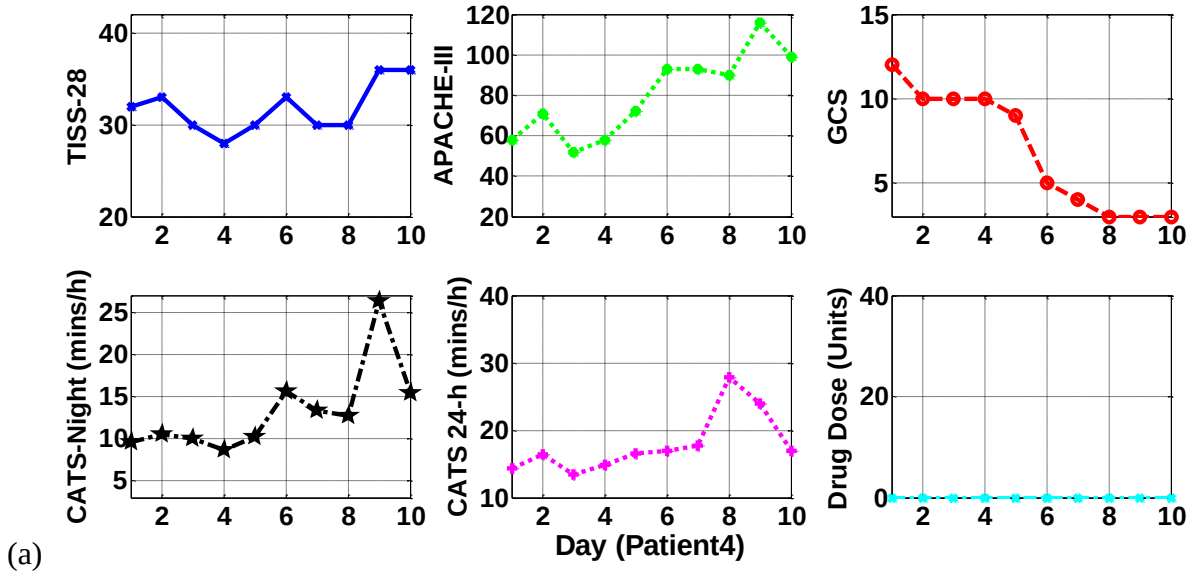
10.3 Temporal progression of nursing workload and acuity scores.

Figure 10.2 (a-f) shows the progression of TISS-28, APACHE-III, avergae nursing time over the night and entire 24 hours, GCS, and sedative dose for all 6 patients. Patients 4, 9, and 11 show an increase acuity (APACHE-III) trend, but only Patient 4 shows an increasing trend in nursing time (CATS-24h). Patients 22 and 23 show a decrease acuity trend, but neither of these 2 patients preserve a decreasing trend in nursing time. It shows that APACHE-III dose

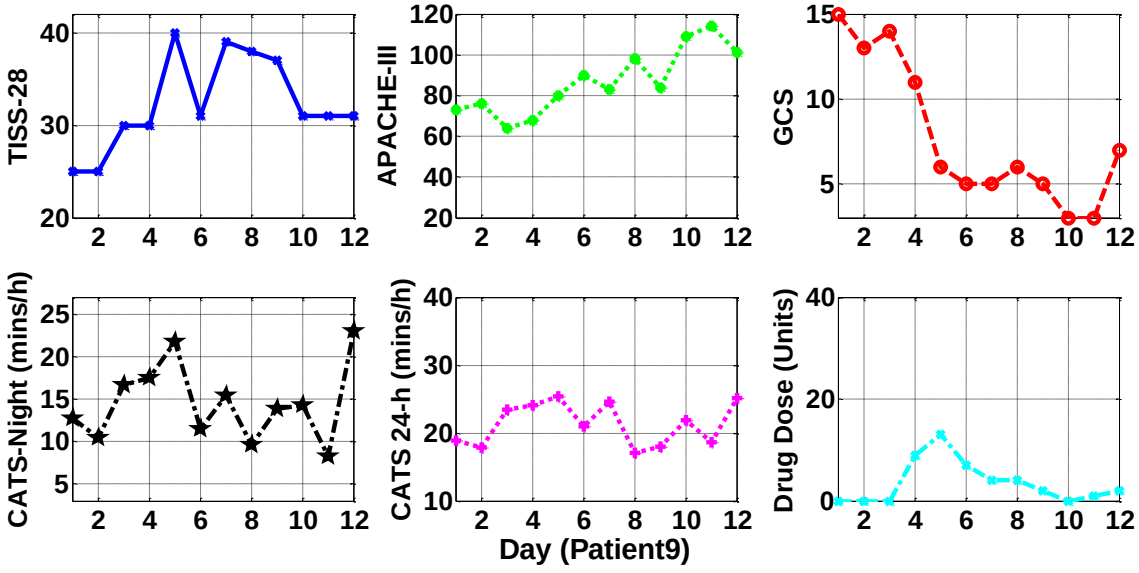
not correlated well with CATS nursing intervention time, as hypothesized at the beginning. Patient 4, 9 and 11 show a decreasing sedation level (GCS) during their stay, but they all have different trends in nursing time. In terms of sedation dose, Paitent 11 is the only patient who shows a negative correaltion between sedation dose and nursing time. None of these 6 patients' TISS-28 scores have a clear correlation with their nursing time.

APACHE-III, TISS-28, GCS, and sedative dose do not have a clear strong correlation with nursing time. CATS is the only objective tool to quantifying real nursing time, and it is difficult to use indirect indicators to assess nursing workload.

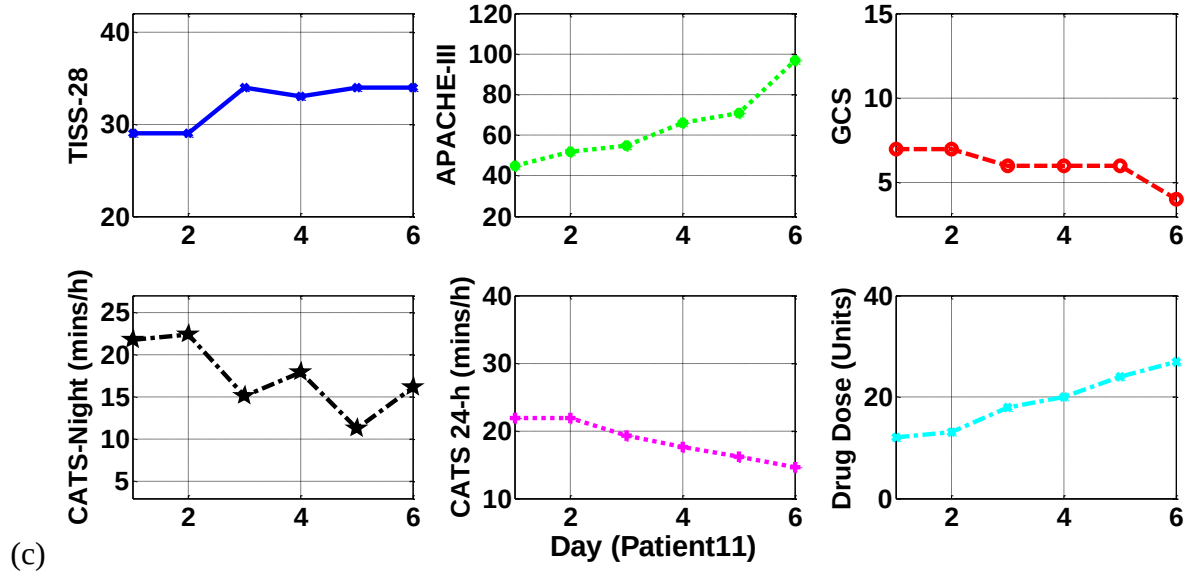
In summary, nursing demands are patient-specific and dependent on several factors. There are thus no clear trends across patient acutiy, sedative drug dosage, patient sedation level, and type of diagnosis. Hence, the consistent and objective activity measure is potentially the most accurate measure of direct nursing activity, paricularly at night where a more limited range of routine tasks are performed.



(a)



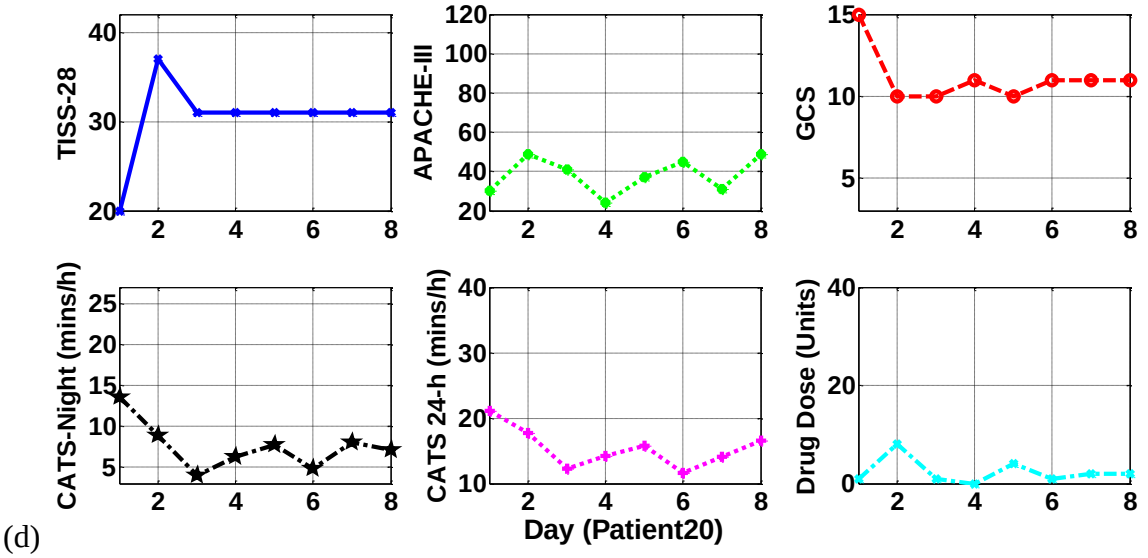
(b)



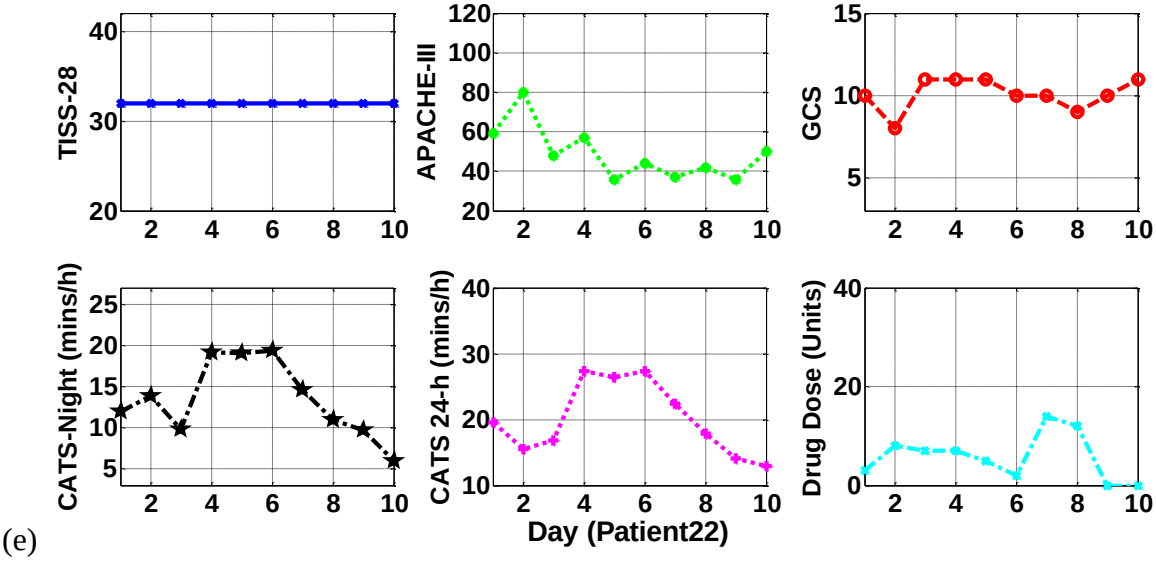
(c)

Figure 10.2 continued next page…

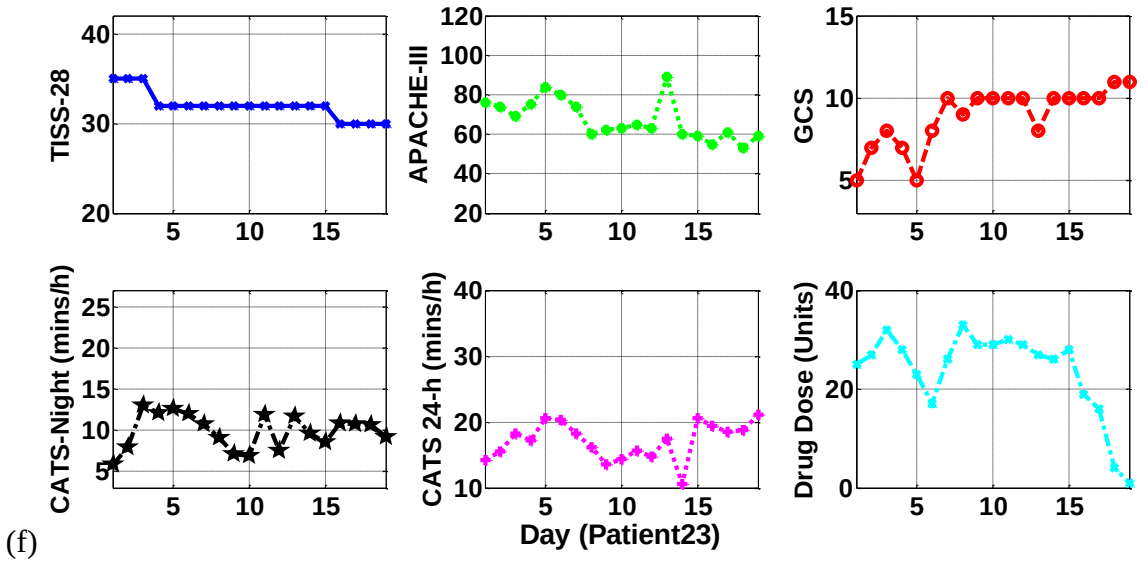
Figure 10.2 continued.



(d)



(e)



(f)

Figure 10.2: TISS-28, APACHE-III, average nursing time over the night and entire day, GCS, and Drug dose during the LOS of patients. 'CATS 24-h' is the average nursing time of 24 hours; 'CATS-Night' is the average nursing time of each night shift.

10.4 Recommended nurse-to-patient ratio

The number of nurses should be adapted to the number of ICU beds and to the likely patient case admistted to the area. The number of beds handled by one nurse must be calculated accroding to the levels of care that need to be delivered to each patient. Nurse-to-patient ratio is one metric for nursing staff requiremnts that has been recommended by many authors [85, 314-317]. The European Society of Intensive Care Medicine (ESICM) classifies nursing care ratios into three levels: 1) Highest (1:1); 2) Median (1:1.6); and 3) Lowest (1:3) [318]. Gallesio et al. [319] categorize patient according to a 4 risk scale: 1) Monitoring; 2) High risk; 3) Critically ill; and 4) Prolonged critically ill. Combining this scale with TISS, and taking into account some special situations, they have calculated, on a twice-daily basis, the nursing care needs for the whole unit accroding to TISS-28. They recommend the following nurse to patient ratios: 1) TISS-28>46 (1:1); 2) TISS-28 18-46 (1:2); and 3) TISS-28 <18 (only for monitoring). However, as shown in this study, TISS-28 has poor resolusion for identifying patient needs, and may not be an accurate reflection of nursing activity or patient demand.

In this study, the APACHE-III and different work shifts are used to develop an estimation of potential nurse-to-patient ratios. According to patient APACHE-III scores, patient acuity levels are divided into 3 groups according to tertiles in the clinical data: APACHE-III≤40, 40<APACHE-III≤80, and APACHE-III>80. In addition, as nursing time at night is more correlated with direct nursing activity for care, it is reasonable to estimate the night nurse-to-patient ratio first. Daytime nurse-to-patient ratio is estimated accoridng to $C_{timeK13}$ (day)=1.4 × $C_{timeK13}$ (night), which has been demonstrated in Chapter 6.

Table 10.2 (a) shows the calculation of nurse-to-patient ratio during the night shift

(23:00~07:00 hours). From Table 10.2 (a), night shift, for patient APACHE-III scores of 40, 80 and 120 respectively, the 95th percentile of $C_{timeK13}$ are 14, 17, and 20 minutes/hour. Using the group 0<APACHE-III<40 as an example, according to $A_{timeK13} = 0.974 \times C_{timeK13} + 6.401$ (Equation 6.1), the actual direct nursing intervention should be $A_{timeK13} = 0.974 \times 14 + 6.401 = 20$ minutes/hour. Also, according to [2], $A_{timeK13}$ is equavilant to direct (Categories 1 and 2) nursing activities. In [2], Table 7 (Appendix 10.1), sum of Categories 1 and Category 2 nursing activities account for 38.3%+11.1%=49.4% of entire nursing time. Thus, entire required nursing time should be 20/49.4%=40 minutes/hour, which means the ideal nurse-to-patient ratio is 60/40=1:1.5. The transition from $C_{timeK13}$ to estimated entire nursing time is thus defined:

$$Entire\ Nursing\ Time\ (Night) = (C_{timeK13}\ (95\%CI) \times 0.974 + 6.401) / 0.494 \quad (10.1)$$

Table 10.2 (b) shows the calculation of nurse-to-patient ratio during day shift (07:00~23:00 hours). It was demonstrated in Chapter 6 that nursing intervention $A_{timeK13}$ during day shift is 1.4 times higher than night shift. In addition, in [2] Table 7 (Appendix 10.1), it suggested Categories 1 and 2 nursing activities accourt for nearly 59% of entire nursing time during the day. Thus, the transition from $C_{timeK13}$ to estimated entire nursing time in the day is:

$$Entire\ Nursing\ Time\ (Day) = (C_{timeK13}\ (95\%CI) \times 0.974 + 6.401) \times 1.4\ / 0.6 \quad (10.2)$$

Table 10.2 (a): Calculation of nurse-to-patient ratio during night shift (23:00~07:00)

	CATS captured in K13 (95th percentile) (mins/h)	Entire Nursing Time (minutes/hour)	N/P ratio
0<APACHE-III<40	14	(14×0.974+6.4)/0.494=40	40/60 = 1:1.5
40<APACHE-III<80	17	(17×0.974+6.4)/0.494=46	46/60 = 1:1.3
APACHE-III>80	20	(20×0.974+6.4)/0.494=52	52/60 = 1:1.2

Table 10.2 (b): Calculation of nurse-to-patient ratio during day shift (07:00~23:00)

	CATS captured in K13 (95th percentile) (mins/h)	Entire Nursing Time (minutes/hour)	N/P ratio
0<APACHE-III<40	14	(14×0.974+6.4)×1.4/0.6=47	47/60 = 1:1.3
40<APACHE-III<80	17	(17×0.974+6.4)×1.4/0.6=54	54/60=1:1.1
APACHE-III>80	20	(20×0.974+6.4)×1.4/0.6=60	60/60 = 1:1

Limitations:

The recommended night time nurse-to-patient ratio is based on the conclusions that $A_{timeK13}$ = 0.974 × $C_{timeK13}$ + 6.401 (Equation 6.1), and that $A_{timeK13}$ only account for 49.4% of entire nursing time during a night shift, as shown in Appendix 10.1. In addition, the recommended daytime nurse-to-patient ratio is based on the conclusions that $A_{timeK13}$ (day)=1.4 × $A_{timeK13}$ (night) in Chapter 6, and that $A_{timeK13}$ only account for 59% of entire nursing time during the day [2]. These conclusions may not truly reflect the clinical conditions. In addition, ICUs vary from hospital to hospital so the Christchurch Hospital ICU may not represent other ICUs.

The results do provide a good first estimate to ICU staff on an optimal nurse-to-patient ratio, considering different patient acuity levels and different times of the day. However, it uses 95th percentile CATS captured $C_{timeK13}$ to estimate the entire nursing time. It thus requires an objective measure (K1 + K3) of direct nursing activity.

In clinical settings, this recommended nurse-to-patient ratio could also be adjusted by other factors, such as patient diagnostic code, chronic disease, patient gender, patient LOS, patient personality, family demands, and ICU specific situations. Thus, further research needs to be conducted, combining all these factors to generate a more optional and clinically acceptable nurse-to-patient chart.

10.5 Summary

In this Chapter, 6 patients with LOS more than 6 days were selected to specifically analyse their nursing demands variation, indicating patient severity, sedative level and type of diagnosis could all affect patient nursing demands. In addition, it generated the recommended nurse-to-patient ratio based on different time of the day and different patient severity level. These results could guide nursing team to optimal allocate nursing resources.

Chapter 11 Conclusions, Limitations and Future work

11.1 Conclusions

This research develops and validates a novel non-intrusive method to quantify direct nursing workload in the ICU. Quantified bedside nursing workload was compared with patient clinical data to identify factors influencing the nursing workload intensity. The conclusions are divided into two parts: 1) the development and validation of CATS presented in Chapters 2 to 6; and 2) the relationship between nursing workload and patient clinical details, as presented in Chapters 7 to 10.

11.1.1 CATS development

In Chapter 2, four different motion tracking methods were examined, including facial detection, color detection, infra-red detection, and local positioning measurement. Their advantages and disadvantages were evaluated. It was found that an infrared depth sensor detection best suits the application in monitoring nursing activity and workload around an ICU bed space, particularly when considering privacy issues. This concept was further developed and implemented in the ICU.

In Chapters 3 and 4, the developments of the CATS hardware and software components were presented. CATS hardware consists of 4 Kinect sensors and 2 laptops, and the software was developed using C++ with ‘OpenNi’ and ‘OpenCV’ libraries. Chapter 4 specifically focused on testing of CATS in a simulated environment. The Kinect was installed on a ceiling of a test area to simulate the clinical environment. Several tests were carried out and the CATS

was able to accurately monitor subject trajectory and time spent in the detection area, including dwell time.

In Chapter 5, the CATS was installed in the Christchurch hospital ICU for clinical testing. Further software development was carried out to adapt CATS for the application in the ICU. In particular, several specific and novel filter algorithms were developed to eliminate noise or disturbances specific to this clinical environment, all of which were classified into broad types. Results showed that the filtering algorithms were able to record and clinical bedside activity, without interference from curtains, clinical machinery, or non-nursing visitors.

In Chapter 6, the nursing intervention captured by CATS was further validated by comparing to direct clinical observation of workload, as a first validation in site. A correlation of CATS captured nursing intervention and observed nursing intervention was generated, and it can be used to generate a surrogate of the actual bedside nursing intervention in automated monitoring. Preliminary results during this first validation process showed that patients are likely to receive higher nursing care, based on time at the bedside, during the day than at night.

11.1.2 Clinical conclusions

In Chapter 7, different patient severity assessment tools and different nursing workload assessment tools were studied. A total 23 patients (104 patient days) included in the CATS monitoring trial were used to calculate TISS-28, NEMS, APACHE-III, SAPS-II, APACHE-II, and SOFA scores. It was found that the APACHE-III score had better resolution to describe patient acuity than SAPS-II, APACHE-II and SOFA. Both TISS-28 and NEMS had very poor resolution in differentiating patient-specific nursing demands.

Chapter 8 presents an analysis of the effect of patient sedative level, measured by RASS, GCS, and sedative drug dose, towards other severity and nursing workload assessment scores. Results showed that the current patient sedation assessment tools were not able to fully capture patient sedative level. No clinical strong correlation is found between nursing time and patient sedation level.

In Chapter 9, nursing workloads derived from CATS were compared with patient clinical results. Results showed that the patient clinical severity has a weak or no correlation with patient nursing demand and time required. It also showed that that nursing workload captured by CATS was not correlated with TISS-28 or NEMS, indicating that both TISS-28 and NEMS were too general, and thus not able to assess patient-specific nursing workload in the study hospital ICU.

Chapter 10 focused on patient specific study of the nursing workload as a function of time and other clinical factors. The results showed that there is no clear correlation between nursing time and patient severity, sedation level. Finally, a hospital ICU specific preliminary nurse-to-patient ratio was calculated based on different time of the day and different patient severity levels.

11.2 Limitations

Nursing time includes direct nursing activities and indirect nursing activities. CATS was only able to quantify the nursing interventions that occur at the patient bedside, which represent direct nursing activities, but not indirect nursing activities. Thus, the correlations were only assessed between the direct nursing activities in K1 +K3 and other clinical assessment scores.

Patient personality and family characteristics may also significantly influence nursing workload. According to the researcher's own observation and communication with nurses, there are cases when two patients may have very similar injuries and similar severity, while their workloads are quite different because different personalities can lead to different nursing demands.

This research is based on 23 patients, covering 104 patient days. Because of the cohort size, the correlation between nursing workload and all other patient clinical factors may not perfectly represent reality. It is necessary to apply this methodology for longer period within various ICUs.

11.3 Future work

The potential future work of this study can be divided into 2 parts. First, further development of nursing tracking system is required to make it more accurate and more nursing focused. Second, more clinical applications are required to make the results more reliable over a larger patient cohort.

11.3.1 Further develop of nursing tracking system

Further improvements to the algorithm can be made to identify and separate nurse and other clinical staffs entering into the bedside area. Currently, other clinical staff and family members are separated in the analysis by their walking patterns, as discussed in Chapter 5. One possible solution is to combine color image and depth image during processing. When a blob is detected, CATS could first detect color image, and if this blob is the same color as a nurse's uniform, system initiates tracking procedure.

Further future work could be carried out in the area of testing the performance of LPM (local positioning measurement) system. It is noted that a LPM could accurately track the time and motion trajectories of a target. This method is capable of knowing each individual nurse's location at all times, and as a result the detection area covers the entire ICU. However, there is concern that this is a more intrusive method in which is dependent on the participating cohort and their consent to the study.

Another significant improvement to the CATS can be made in the development of a wireless, real-time tracking system. Currently, Kinect sensors are connected to laptops via cables, which occupy the already busy patient bedside. With more applications of general-purpose single-chip microcomputers [320] and wireless communication [321], it is possible to improve current systems controlling the Kinect sensors by running them off a single-chip microcomputer.

The forth major area of future work would be differentiating specific nursing activities. CATS has potential to detect more specific information, such as people's skeleton [322] and hand gestures [323]. Hand gesture detection could possibly recognise which nursing activity is being carried out. Thus, it is possible to know the percentage of total nursing activities on a patient and/or condition specific basis.

11.3.2 Clinical future works

The next step clinical future work is to analyse CATS detection of nursing activities with a larger patient cohort. As noted in the limitation section, this study only included 23 patients, 104 patient days' of clinical data. Correlation between nursing workload and patient clinical information, such as age, gender, severity, and sedation, may not truly correspond to clinical

reality. Increasing the cohort and sample size will provide an opportunity to further verify the findings derived from this study.

The second clinical future work is to apply this approach at different ICUs, either within or between hospitals. As discussed in Chapter 9, different types of ICU may result in different nursing demands, therefore, the recommended nurse-to-patient ratio may not suit other ICUs or hospitals. Thus, it is necessary to test whether these results are universal and whether the recommended nurse-to-patient ratio is applicable to other ICUs.

Finally, clinical future work could also include development of a weighting system to evaluate the impact of patient-specific clinical information to the total nursing time. It is necessary to include other factors, such as patient gender, patient sedative level, and patient diagnosis. Thus, the nursing workload intensity can be written as a function of other clinical factors.

References

[1] A. G. P.D.Lumb, "Intensive and Critical Care Medicine: Reflections, Recommendations and Perspectives," p. 60, 2005.

[2] D. Reis Miranda, A. de Rijk, and W. Schaufeli, "Simplified Therapeutic Intervention Scoring System: The TISS-28 items--Results from a multicenter study," *Critical Care Medicine,* vol. 24, pp. 64-73, 1996.

[3] http://www.chestercountyhospital.org/cchpage.asp?p=1525&m=2213.

[4] R. Moreno and D. R. Miranda, "Nursing staff in intensive care in Europe: the mismatch between planning and practice," *CHEST Journal,* vol. 113, pp. 752-758, 1998.

[5] P. Greco, H. K. S. Laschinger, and C. Wong, "Leader empowering behaviours, staff nurse empowerment and work engagement/burnout," *Nursing Leadership,* vol. 19, pp. 41-56, 2006.

[6] E. Litvak, P. I. Buerhaus, F. Davidoff, M. C. Long, M. L. McManus, and D. M. Berwick, "Managing unnecessary variability in patient demand to reduce nursing stress and improve patient safety," *Joint Commission Journal on Quality and Patient Safety,* vol. 31, pp. 330-338, 2005.

[7] G. J. Tamayo, A. Broxson, M. Munsell, and M. Z. Cohen, "Caring for the caregiver," in *Oncology nursing forum*, 2010, pp. E50-7.

[8] S. Coomber, C. Todd, G. Park, P. Baxter, J. Firth‐Cozens, and S. Shore, "Stress in UK intensive care unit doctors," *British journal of anaesthesia,* vol. 89, pp. 873-881, 2002.

[9] R. Vreeland and G. L. Ellis, "Stresses on the nurse in an intensive-care unit," *AORN Journal,* vol. 10, pp. 54-56, 1969.

[10] M. L. Mealer, A. Shelton, B. Berg, B. Rothbaum, and M. Moss, "Increased prevalence of post-traumatic stress disorder symptoms in critical care nurses," *American Journal of Respiratory and Critical Care Medicine,* vol. 175, pp. 693-697, 2007.

[11] J. R. Curtis and J.-L. Vincent, "Ethics and end-of-life care for adults in the intensive care unit," *The Lancet,* vol. 376, pp. 1347-1353, 2010.

[12] M. Verdon, P. Merlani, T. Perneger, and B. Ricou, "Burnout in a surgical ICU team," *Intensive Care Medicine,* vol. 34, pp. 152-156, 2008.

[13] N. Embriaco, E. Azoulay, K. Barrau, N. Kentish, F. Pochard, A. Loundou*, et al.*, "High level of burnout in intensivists: prevalence and associated factors," *American Journal of Respiratory and Critical Care Medicine,* vol. 175, pp. 686-692, 2007.

[14] B. Ricou and P. Merlani, "[Burnout in intensive care units]," *Revue medicale suisse,* vol. 8, pp. 2400-2, 2404, 2012.

[15] N. Embriaco, L. Papazian, N. Kentish-Barnes, F. Pochard, and E. Azoulay, "Burnout syndrome among critical care healthcare workers," *Current opinion in critical care,* vol. 13, pp. 482-488, 2007.

[16] T. Shanafelt and L. Dyrbye, "Oncologist burnout: causes, consequences, and responses," *Journal of clinical oncology : official journal of the American Society of Clinical Oncology,* vol. 30, pp. 1235-1241, 2012/04// 2012.

[17] L. H. Aiken, D. M. Sloane, S. Clarke, L. Poghosyan, E. Cho, L. You*, et al.*, "Importance of work environments on hospital outcomes in nine countries," *International Journal for Quality in Health Care,* vol. 23, pp. 357-364, 2011.

[18] L. F. Zhang, L. M. You, K. Liu, J. Zheng, J. B. Fang, M. M. Lu*, et al.*, "The association of Chinese hospital work environment with nurse burnout, job satisfaction, and intention to leave," *Nursing outlook,* vol. 62, pp. 128-137, Mar-Apr 2014.

[19] A. Nantsupawat, W. Srisuphan, W. Kunaviktikul, O. A. Wichaikhum, Y. Aungsuroch, and L. H. Aiken, "Impact of nurse work environment and staffing on hospital nurse and quality of care in Thailand," *Journal of Nursing Scholarship,* vol. 43, pp. 426-432, 2011.

[20] L. Tourigny, V. V. Baba, and X. Wang, "Burnout and depression among nurses in Japan and China: The moderating effects of job satisfaction and absence," *The International Journal of Human Resource Management,* vol. 21, pp. 2741-2761, 2010.
[21] L. H. Aiken, S. P. Clarke, D. M. Sloane, J. A. Sochalski, R. Busse, H. Clarke*, et al.*, "Nurses' reports on hospital care in five countries," *Health Affairs,* vol. 20, pp. 43-53, 2001.
[22] M. C. Poncet, P. Toullic, L. Papazian, N. Kentish-Barnes, J.-F. Timsit, F. Pochard*, et al.*, "Burnout syndrome in critical care nursing staff," *American Journal of Respiratory and Critical Care Medicine,* vol. 175, pp. 698-704, 2007.
[23] D. K. McNeese-Smith, "The influence of manager behavior on nurses' job satisfaction, productivity, and commitment," *Journal of Nursing Administration,* vol. 27, pp. 47-55, 1997.
[24] A. D. Ackerman, "Retention of critical care staff," *Critical Care Medicine,* vol. 21, p. S394, 1993.
[25] http://bestcareermatch.com/burnout-checklist.
[26] L. H. Aiken, S. P. Clarke, D. M. Sloane, J. Sochalski, and J. H. Silber, "Hospital nurse staffing and patient mortality, nurse burnout, and job dissatisfaction," *JAMA,* vol. 288, pp. 1987-93, Oct 23-30 2002.
[27] J. N. Scanlan and M. Still, "Job satisfaction, burnout and turnover intention in occupational therapists working in mental health," *Australian Occupational Therapy Journal,* vol. 60, pp. 310-318, Oct 2013.
[28] H. Figueiredo-Ferraz, E. Grau-Alberola, P. R. Gil-Monte, and J. A. Garcia-Juesas, "Burnout and job satisfaction among nursing professionals," *Psicothema,* vol. 24, pp. 271-276, May 2012.
[29] W. O. Tarnow-Mordi, C. Hau, A. Warden, and A. J. Shearer, "Hospital mortality in relation to staff workload: a 4-year study in an adult intensive-care unit," *The Lancet,* vol. 356, pp. 185-189, 7/15/ 2000.
[30] L. H. Aiken, D. M. Sloane, L. Bruyneel, K. Van den Heede, P. Griffiths, R. Busse*, et al.*, "Nurse staffing and education and hospital mortality in nine European countries: a retrospective observational study," *The Lancet,* vol. 383, pp. 1824-1830, 2014.
[31] K. Van den Heede, E. Lesaffre, L. Diya, A. Vleugels, S. P. Clarke, L. H. Aiken*, et al.*, "The relationship between inpatient cardiac surgery mortality and nurse numbers and educational level: analysis of administrative data," *International Journal of Nursing Studies,* vol. 46, pp. 796-803, 2009.
[32] M. Schubert, S. P. Clarke, L. H. Aiken, and S. De Geest, "Associations between rationing of nursing care and inpatient mortality in Swiss hospitals," *International Journal for Quality in Health Care,* vol. 24, pp. 230-238, 2012.
[33] R. L. Kane, T. A. Shamliyan, C. Mueller, S. Duval, and T. J. Wilt, "The association of registered nurse staffing levels and patient outcomes: systematic review and meta-analysis," *Medical Care,* vol. 45, pp. 1195-1204, 2007.
[34] R. Lee Taunton, S. V. M. Kleinbeck, R. Stafford, C. Q. Woods, and M. J. Bott, "Patient Outcomes: Are They Linked to Registered Nurse Absenteeism, Separation, or Work Load?," *Journal of Nursing Administration,* vol. 24, pp. 48-55, 1994.
[35] T. A. Lang, M. Hodge, V. Olson, P. S. Romano, and R. L. Kravitz, "Nurse–patient ratios: a systematic review on the effects of nurse staffing on patient, nurse employee, and hospital outcomes," *Journal of Nursing Administration,* vol. 34, pp. 326-337, 2004.
[36] S.-H. Cho, S. Ketefian, V. H. Barkauskas, and D. G. Smith, "The effects of nurse staffing on adverse events, morbidity, mortality, and medical costs," *Nursing Research,* vol. 52, pp. 71-79, 2003.
[37] L. K. Lichtig, R. A. Knauf, and D. K. Milholland, "Some impacts of nursing on acute care hospital outcomes," *Journal of Nursing Administration,* vol. 29, pp. 25-33, 1999.
[38] H. Sax and D. Pittet, "Interhospital differences in nosocomial infection rates: importance of case-mix adjustment," *Archives of internal medicine,* vol. 162, pp. 2437-2442, 2002.

[39] M. Singer, S. Myers, G. Hall, S. Cohen, and R. Armstrong, "The cost of intensive care: a comparison on one unit between 1988 and 1991," *Intensive Care Medicine,* vol. 20, pp. 542-549, 1994.

[40] W. A. Knaus, D. P. Wagner, J. E. Zimmerman, and E. A. Draper, "Variations in mortality and length of stay in intensive care units," *Annals of Internal Medicine,* vol. 118, pp. 753-761, 1993.

[41] M. Sznajder, G. Leleu, G. Buonamico, B. Auvert, P. Aegerter, Y. Merliere*, et al.*, "Estimation of direct cost and resource allocation in intensive care: correlation with Omega system," *Intensive Care Medicine,* vol. 24, pp. 582-589, 1998.

[42] D. D. Emery and L. J. Schneiderman, "Cost‐Effectiveness Analysis in Health Care," *Hastings Center Report,* vol. 19, pp. 8-13, 1989.

[43] N. A. Halpern, "Can the costs of critical care be controlled?," *Current opinion in critical care,* vol. 15, pp. 591-596, 2009.

[44] H. Dickie, A. Vedio, R. Dundas, D. F. Treacher, and R. M. Leach, "Relationship between TISS and ICU cost," *Intensive Care Medicine,* vol. 24, pp. 1009-1017, 1998/10/01 1998.

[45] D. R. Miranda, "The therapeutic intervention scoring system: one single tool for the evaluation of workload, the work process and management?," *Intensive Care Medicine,* vol. 23, pp. 615-617, 1997/06/01 1997.

[46] S. S. Tan, L. Hakkaart-van Roijen, M. J. Al, C. A. Bouwmans, M. E. Hoogendoorn, P. E. Spronk*, et al.*, "A microcosting study of intensive care unit stay in the Netherlands," *Journal of intensive care medicine,* 2008.

[47] M. Jegers, "Budgeting and cost accounting in European intensive care units: a note," *Financial Accountability & Management,* vol. 12, pp. 323-334, 1996.

[48] D. L. Edbrooke, C. L. Hibbert, J. M. Kingsley, S. Smith, N. M. Bright, and J. M. Quinn, "The patient-related costs of care for sepsis patients in a United Kingdom adult general intensive care unit," *Critical Care Medicine,* vol. 27, pp. 1760-1767, 1999.

[49] A. R. Neilson, O. Moerer, H. Burchardi, and H. Schneider, "A new concept for DRG-based reimbursement of services in German intensive care units: results of a pilot study," *Intensive Care Medicine,* vol. 30, pp. 1220-1223, 2004.

[50] M. Sznajder, P. Aegerter, R. Launois, Y. Merliere, B. Guidet, and V. CubRea, "A cost-effectiveness analysis of stays in intensive care units," *Intensive Care Medicine,* vol. 27, pp. 146-153, 2001.

[51] H. Flaatten and R. Kvåle, "Cost of intensive care in a Norwegian University hospital 1997–1999," *Critical Care,* vol. 7, p. 72, 2002.

[52] J. Graf, C. Graf, and U. Janssens, "Analysis of resource use and cost-generating factors in a German medical intensive care unit employing the Therapeutic Intervention Scoring System (TISS-28)," *Intensive Care Medicine,* vol. 28, pp. 324-331, 2002.

[53] Á. Csomós, M. Janecskó, and D. Edbrooke, "Comparative costing analysis of intensive care services between Hungary and United Kingdom," *Intensive Care Medicine,* vol. 31, pp. 1280-1283, 2005.

[54] D. T. Yu, E. Black, K. E. Sands, J. S. Schwartz, P. L. Hibberd, P. S. Graman*, et al.*, "Severe sepsis: variation in resource and therapeutic modality use among academic centers," *Critical Care,* vol. 7, p. R24, 2003.

[55] I. Rechner and J. Lipman, "The costs of caring for patients in a tertiary referral Australian Intensive Care Unit," *Anaesthesia and Intensive Care,* vol. 33, p. 477, 2005.

[56] U. Obertacke, F. Neudeck, H. Wihs, and K. Schmit-Neuerburg, "[Cost analysis of primary care and intensive care treatment of multiple trauma patients]," *Der Unfallchirurg,* vol. 100, pp. 44-49, 1997.

[57] D. Teres, J. Rapoport, S. Lemeshow, S. Kim, and K. Akhras, "Effects of severity of illness on resource use by survivors and nonsurvivors of severe sepsis at intensive care unit admission*," *Critical Care Medicine,* vol. 30, pp. 2413-2419, 2002.

[58] J. Rapoport, D. Teres, S. Lemeshow, J. S. Avrunin, and R. Haber, "Explaining variability of cost using a severity-of-illness measure for ICU patients," *Medical Care,* vol. 28, pp. 338-348, 1990.

[59] T. L. Higgins, W. T. McGee, J. S. Steingrub, J. Rapoport, S. Lemeshow, and D. Teres, "Early indicators of prolonged intensive care unit stay: Impact of illness severity, physician staffing, and pre–intensive care unit length of stay," *Critical Care Medicine,* vol. 31, pp. 45-51, 2003.

[60] O. Moerer, A. Schmid, M. Hofmann, A. Herklotz, K. Reinhart, K. Werdan*, et al.*, "Direct costs of severe sepsis in three German intensive care units based on retrospective electronic patient record analysis of resource use," *Intensive Care Medicine,* vol. 28, pp. 1440-1446, 2002.

[61] P. Thungjaroenkul, W. Kunaviktikul, P. Jacobs, G. G. Cummings, and T. Akkadechanunt, "Nurse staffing and cost of care in adult intensive care units in a university hospital in Thailand," *Nursing & Health Sciences,* vol. 10, pp. 31-36, 2008.

[62] C. A. Estabrooks, W. K. Midodzi, G. G. Cummings, K. L. Ricker, and P. Giovannetti, "The impact of hospital nursing characteristics on 30‐day mortality," *Nursing Research,* vol. 54, pp. 74-84, 2005.

[63] J. Needleman, P. I. Buerhaus, S. Mattke, M. Stewart, and K. Zelevinsky, "Measuring Hospital Quality: Can Medicare Data Substitute for All‐Payer Data?," *Health Services Research,* vol. 38, pp. 1487-1508, 2003.

[64] A. E. Tourangeau, D. M. Doran, L. M. Hall, L. O'Brien Pallas, D. Pringle, J. V. Tu*, et al.*, "Impact of hospital nursing care on 30‐day mortality for acute medical patients," *Journal of Advanced Nursing,* vol. 57, pp. 32-44, 2007.

[65] J. F. Dasta, T. P. McLaughlin, S. H. Mody, and C. T. Piech, "Daily cost of an intensive care unit day: The contribution of mechanical ventilation*," *Critical Care Medicine,* vol. 33, pp. 1266-1271, 2005.

[66] J. Rapoport, D. Teres, Y. Zhao, and S. Lemeshow, "Length of stay data as a guide to hospital economic performance for ICU patients," *Medical Care,* vol. 41, pp. 386-397, 2003.

[67] D. M. Needham and P. J. Pronovost, "The importance of understanding the costs of critical care and mechanical ventilation*," *Critical Care Medicine,* vol. 33, pp. 1434-1435, 2005.

[68] C. Adrie, C. Alberti, C. Chaix-Couturier, É. Azoulay, A. de Lassence, Y. Cohen*, et al.*, "Epidemiology and economic evaluation of severe sepsis in France: age, severity, infection site, and place of acquisition (community, hospital, or intensive care unit) as determinants of workload and cost," *Journal of Critical Care,* vol. 20, pp. 46-58, 2005.

[69] C. E. Cox, S. S. Carson, J. H. Lindquist, M. K. Olsen, J. A. Govert, L. Chelluri*, et al.*, "Differences in one-year health outcomes and resource utilization by definition of prolonged mechanical ventilation: a prospective cohort study," *Crit Care,* vol. 11, p. R9, 2007.

[70] K. G. Padilha, R. M. C. de Sousa, P. C. Garcia, S. T. Bento, E. M. Finardi, and R. H. K. Hatarashi, "Nursing workload and staff allocation in an intensive care unit: A pilot study according to Nursing Activities Score (NAS)," *Intensive and Critical Care Nursing,* vol. 26, pp. 108-113, 4// 2010.

[71] C. P. Landrigan, J. M. Rothschild, J. W. Cronin, R. Kaushal, E. Burdick, J. T. Katz*, et al.*, "Effect of reducing interns' work hours on serious medical errors in intensive care units," *New England Journal of Medicine,* vol. 351, pp. 1838-1848, 2004.

[72] M. Hughes, "Nursing workload: an unquantifiable entity," *Journal of Nursing Management,* vol. 7, pp. 317-322, 1999.

[73] P. Hoonakker, P. Carayon, A. Gurses, R. Brown, K. McGuire, A. Khunlertkit*, et al.*, "Measuring Workload of Icu Nurses with a Questionnaire Survey: The Nasa Task Load Index (Tlx)," *IIE Trans Healthc Syst Eng,* vol. 1, pp. 131-143, 2011.

[74] R. Morris, P. MacNeela, A. Scott, P. Treacy, and A. Hyde, "Reconsidering the conceptualization of nursing workload: literature review," *Journal of Advanced Nursing,* vol. 57, pp. 463-471, 2007.

[75] R. J. Lysaght, S. G. Hill, A. Dick, B. D. Plamondon, and P. M. Linton, "Operator workload: Comprehensive review and evaluation of operator workload methodologies," DTIC Document1989.
[76] R. W. Backs, A. M. Ryan, and G. F. Wilson, "Psychophysiological measures of workload during continuous manual performance," *Human Factors: The Journal of the Human Factors and Ergonomics Society,* vol. 36, pp. 514-531, 1994.
[77] M. B. Weinger, S. B. Reddy, and J. M. Slagle, "Multiple measures of anesthesia workload during teaching and nonteaching cases," *Anesthesia & Analgesia,* vol. 98, pp. 1419-1425, 2004.
[78] D. R. Miranda, "Nursing activities score," *Critical Care Medicine,* vol. 31, pp. 374-382, 2003.
[79] G. Iapichino, "Time oriented score system (TOSS): A method for direct and quantitative assessment of nursing workload for ICU patients," *Intensive Care Medicine,* vol. 17, pp. 340-345, 1991.
[80] L. A. Goncalves, K. G. Padilha, and R. M. Cardoso Sousa, "Nursing activities score (NAS): a proposal for practical application in intensive care units," *Intensive Crit Care Nurs,* vol. 23, pp. 355-61, Dec 2007.
[81] Cullen, "Therapeutic intervention scoring system: a method for quantitative comparison of patient care," *Critical Care Medicine,* vol. 2, pp. 57-60, 1974.
[82] Keene, "Therapeutic Intervention Scoring System: Update 1983," *Critical Care Medicine,* vol. 11, pp. 1-3, 1983.
[83] P. Carayon and A. P. Gürses, "A human factors engineering conceptual framework of nursing workload and patient safety in intensive care units," *Intensive and Critical Care Nursing,* vol. 21, pp. 284-301, 10// 2005.
[84] P. Carayon and A. P. Gurses, "A human factors engineering conceptual framework of nursing workload and patient safety in intensive care units," *Intensive Crit Care Nurs,* vol. 21, pp. 284-301, Oct 2005.
[85] R. Adomat and A. Hewison, "Assessing patient category/dependence systems for determining the nurse/patient ratio in ICU and HDU: a review of approaches," *Journal of Nursing Management,* vol. 12, pp. 299-308, 2004.
[86] D. R. Miranda, R. Moreno, and G. Iapichino, "Nine equivalents of nursing manpower use score (NEMS)," *Intensive Care Medicine,* vol. 23, pp. 760-765, 1997/07/01 1997.
[87] R. Adomat and C. Hicks, "Measuring nursing workload in intensive care: an observational study using closed circuit video cameras," *Journal of Advanced Nursing,* vol. 42, pp. 402-412, 2003.
[88] M. Vossiek, L. Wiebking, P. Gulden, J. Weighardt, and C. Hoffmann, "Wireless local positioning-concepts, solutions, applications," in *Radio and Wireless Conference, 2003. RAWCON'03. Proceedings*, 2003, pp. 219-224.
[89] E. Kaplan and C. Hegarty, *Understanding GPS: principles and applications*: Artech house, 2005.
[90] A. K. Brown and M. A. Sturza, "GPS tracking system," ed: Google Patents, 1995.
[91] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on,* vol. 37, pp. 1067-1080, 2007.
[92] C. M. Roberts, "Radio frequency identification (RFID)," *Computers & Security,* vol. 25, pp. 18-26, 2006.
[93] J. J. Caffery and G. L. Stuber, "Overview of radiolocation in CDMA cellular systems," *Communications Magazine, IEEE,* vol. 36, pp. 38-45, 1998.
[94] K. Siwiak, "Ultra-wide band radio: introducing a new technology," in *Vehicular Technology Conference, 2001. VTC 2001 Spring. IEEE VTS 53rd*, 2001, pp. 1088-1093.
[95] S. Messenger, "Wireless local area network," ed: Google Patents, 1991.

[96] J. C. Haartsen, "The Bluetooth radio system," *Personal Communications, IEEE,* vol. 7, pp. 28-36, 2000.
[97] P. Bauwens, "Ultra-high frequency," *British Medical Journal,* vol. 2, p. 328, 1936.
[98] S. G. Clark, "Ultra high frequency signaling," ed: Google Patents, 1939.
[99] M. Zeng, J. Li, and Z. Peng, "The design of Top-Hat morphological filter and application to infrared target detection," *Infrared Physics & Technology,* vol. 48, pp. 67-76, 4// 2006.
[100] G. Bradski and A. Kaehler, *Learning OpenCV: Computer Vision with the OpenCV Library*: O'Reilly Media, 2008.
[101] K. G. Padilha, R. M. C. Sousa, M. Kimura, A. M. K. Miyadahira, D. A. L. M. da Cruz, M. d. F. Vattimo*, et al.*, "Nursing workload in intensive care units: A study using the Therapeutic Intervention Scoring System-28 (TISS-28)," *Intensive and Critical Care Nursing,* vol. 23, pp. 162-169, 6// 2007.
[102] A. O. M. Campagner, P. C. R. Garcia, and J. P. Piva, "Use of scores to calculate the nursing workload in a pediatric intensive care unit," *Revista Brasileira de Terapia Intensiva,* vol. 26, pp. 36-43, Jan-Mar 08/05/received 01/14/accepted 2014.
[103] K. G. Padilha, R. M. C. de Sousa, A. F. Queijo, A. M. Mendes, and D. R. Miranda, "Nursing Activities Score in the intensive care unit: Analysis of the related factors," *Intensive and Critical Care Nursing,* vol. 24, pp. 197-204, 6// 2008.
[104] S. Gerasimou-Angelidi, P. Myrianthefs, A. Chovas, G. Baltopoulos, and A. Komnos, "Nursing Activities Score as a predictor of family satisfaction in an adult Intensive Care Unit in Greece," *J Nurs Manag,* vol. 22, pp. 151-8, Mar 2014.
[105] D. P. Olsen, J. K. Dixon, M. Grey, T. Deshefy-Longhi, and J. C. Demarest, "Privacy Concerns of Patients and Nurse Practitioners in Primary Care—An APRNet Study," *Journal of the American Academy of Nurse Practitioners,* vol. 17, pp. 527-534, 2005.
[106] R. Adomat, "Filming in hospitals: Ethical and methodological issues," *Nursing Standard,* vol. 14, pp. 37-9, Sep 29-Oct 5, 1999-09-26 1999.
[107] M. Rashid, "Developing Scales to Evaluate Staff Perception of the Effects of the Physical Environment on Patient Comfort, Patient Safety, Patient Privacy, Family Integration With Patient Care, and Staff Working Conditions in Adult Intensive Care Units: A Pilot Study," *Critical Care Nursing Quarterly,* vol. 30, pp. 271-283, 2007.
[108] P. J. Stow, G. K. Hart, T. Higlett, C. George, R. Herkes, D. McWilliam*, et al.*, "Development and implementation of a high-quality clinical database: the Australian and New Zealand Intensive Care Society Adult Patient Database," *Journal of Critical Care,* vol. 21, pp. 133-141, 6// 2006.
[109] M. Saeed, M. Villarroel, A. T. Reisner, G. Clifford, L.-W. Lehman, G. Moody*, et al.*, "Multiparameter Intelligent Monitoring in Intensive Care II (MIMIC-II): A public-access intensive care unit database," *Critical Care Medicine,* vol. 39, pp. 952-960, 2011.
[110] "Patient volume, staffing, and workload in relation to risk-adjusted outcomes in a random stratified sample of UK neonatal intensive care units: a prospective evaluation," *The Lancet,* vol. 359, pp. 99-107, 1/12/ 2002.
[111] F. Lin, W. Chaboyer, and M. Wallis, "A literature review of organisational, individual and teamwork factors contributing to the ICU discharge process," *Australian Critical Care,* vol. 22, pp. 29-43, 2// 2009.
[112] Z. Liao, "Real-time taxi dispatching using Global Positioning Systems," *Commun. ACM,* vol. 46, pp. 81-83, 2003.
[113] M. A. P. Taylor, J. E. Woolley, and R. Zito, "Integration of the global positioning system and geographical information systems for traffic congestion studies," *Transportation Research Part C: Emerging Technologies,* vol. 8, pp. 257-285, 2// 2000.
[114] R. Zito, G. D'Este, and M. A. P. Taylor, "Global positioning systems in the time domain: How useful a tool for intelligent vehicle-highway systems?," *Transportation Research Part C: Emerging Technologies,* vol. 3, pp. 193-209, 8// 1995.

[115] D. S. Sprague, A. Tiwari, and A. Woo, "Global position system receiver with map coordinate system outputs," ed: Google Patents, 1995.
[116] D. Levy, "System and method for controlling speed of a moving vehicle," ed: Google Patents, 2010.
[117] D. J. Geise and K. G. Croteau, "System to navigate within images spatially referenced to a computed space," ed: Google Patents, 2010.
[118] K. Tomizawa, "Navigation device, method, and program," ed: Google Patents, 2009.
[119] L. Zhao, M. Kohlmann, P. A. Conflitti, R. Brockenbrough, C. S. Conroy, L. Sheynblat*, et al.*, "Navigation receiver," ed: Google Patents, 2013.
[120] A. Stelzer, K. Pourvoyeur, and A. Fischer, "Concept and application of LPM - a novel 3-D local position measurement system," *Microwave Theory and Techniques, IEEE Transactions on,* vol. 52, pp. 2664-2669, 2004.
[121] M. Vossiek, L. Wiebking, P. Gulden, J. Weighardt, and C. Hoffmann, "Wireless local positioning - concepts, solutions, applications," in *Radio and Wireless Conference, 2003. RAWCON '03. Proceedings*, 2003, pp. 219-224.
[122] M. Vossiek, R. Roskosch, and P. Heide, "Precise 3-D Object Position Tracking using FMCW Radar," in *Microwave Conference, 1999. 29th European*, 1999, pp. 234-237.
[123] B. Waldmann, R. Weigel, and P. Gulden, "Method for high precision local positioning radar using an ultra wideband technique," in *Microwave Symposium Digest, 2008 IEEE MTT-S International*, 2008, pp. 117-120.
[124] L. Hui, H. Darabi, P. Banerjee, and L. Jing, "Survey of Wireless Indoor Positioning Techniques and Systems," *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on,* vol. 37, pp. 1067-1080, 2007.
[125] R. Mosshammer, M. Huemer, R. Szumny, K. Kurek, J. Huttner, and R. Gierlich, "A 5.8 GHz Local Positioning and Communication System," in *Microwave Symposium, 2007. IEEE/MTT-S International*, 2007, pp. 1237-1240.
[126] J. Hightower, R. Want, and G. Borriello, "SpotON: An indoor 3D location sensing technology based on RF signal strength," *UW CSE 00-02-02,* // 2000.
[127] L. Ni, Y. Liu, Y. Lau, and A. Patil, "LANDMARC: Indoor Location Sensing Using Active RFID," *Wireless Networks,* vol. 10, pp. 701-710, 2004/11/01 2004.
[128] N. Patwari and J. Wilson, "RF Sensor Networks for Device-Free Localization: Measurements, Models, and Algorithms," *Proceedings of the IEEE,* vol. 98, pp. 1961-1973, 2010.
[129] P. Bahl and V. N. Padmanabhan, "RADAR: an in-building RF-based user location and tracking system," in *INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, 2000, pp. 775-784 vol.2.
[130] M. Kanso and M. Rabbat, "Compressed RF Tomography for Wireless Sensor Networks: Centralized and Decentralized Approaches," in *Distributed Computing in Sensor Systems*. vol. 5516, B. Krishnamachari, S. Suri, W. Heinzelman, and U. Mitra, Eds., ed: Springer Berlin Heidelberg, 2009, pp. 173-186.
[131] V. Otsason, A. Varshavsky, A. LaMarca, and E. de Lara, "Accurate GSM Indoor Localization," in *UbiComp 2005: Ubiquitous Computing*. vol. 3660, M. Beigl, S. Intille, J. Rekimoto, and H. Tokuda, Eds., ed: Springer Berlin Heidelberg, 2005, pp. 141-158.
[132] S. Gezici, T. Zhi, G. B. Giannakis, H. Kobayashi, A. F. Molisch, H. V. Poor*, et al.*, "Localization via ultra-wideband radios: a look at positioning aspects for future sensor networks," *Signal Processing Magazine, IEEE,* vol. 22, pp. 70-84, 2005.
[133] R. J. Fontana, "Recent system applications of short-pulse ultra-wideband (UWB) technology," *Microwave Theory and Techniques, IEEE Transactions on,* vol. 52, pp. 2087-2104, 2004.
[134] R. J. Fontana, E. Richley, and J. Barney, "Commercialization of an ultra wideband precision asset location system," in *Ultra Wideband Systems and Technologies, 2003 IEEE Conference on*, 2003, pp. 369-373.

[135] M. A. Youssef, A. Agrawala, and A. Udaya Shankar, "WLAN location determination via clustering and probability distributions," in *Pervasive Computing and Communications, 2003. (PerCom 2003). Proceedings of the First IEEE International Conference on*, 2003, pp. 143-150.

[136] T. Roos, P. Myllymäki, H. Tirri, P. Misikangas, and J. Sievänen, "A Probabilistic Approach to WLAN User Location Estimation," *International Journal of Wireless Information Networks,* vol. 9, pp. 155-164, 2002/07/01 2002.

[137] T. L. N. R. Battiti, and A. Villani, "Location-aware computing: A neural network model for determining location in wireless LANs," *Tech. Rep.DIT,* vol. 02–0083, 2002.

[138] A. M. Ladd, K. E. Bekris, G. Marceau, A. Rudys, D. S. Wallach, and L. E. Kavraki, "Using wireless Ethernet for localization," in *Intelligent Robots and Systems, 2002. IEEE/RSJ International Conference on*, 2002, pp. 402-408 vol.1.

[139] A. M. Ladd, K. E. Bekris, A. P. Rudys, D. S. Wallach, and L. E. Kavraki, "On the feasibility of using wireless ethernet for indoor localization," *IEEE Transactions on Robotics and Automation,* vol. 20, pp. 555-559, 2004.

[140] A. Haeberlen, E. Flannery, A. M. Ladd, A. Rudys, D. S. Wallach, and L. E. Kavraki, "Practical robust localization over large-scale 802.11 wireless networks," presented at the Proceedings of the 10th annual international conference on Mobile computing and networking, Philadelphia, PA, USA, 2004.

[141] J. Hallberg, M. Nilsson, and K. Synnes, "Positioning with Bluetooth," in *Telecommunications, 2003. ICT 2003. 10th International Conference on*, 2003, pp. 954-958 vol.2.

[142] A. Kotanen, M. Hannikainen, H. Leppakoski, and T. D. Hamalainen, "Experiments on local positioning with Bluetooth," in *Information Technology: Coding and Computing [Computers and Communications], 2003. Proceedings. ITCC 2003. International Conference on*, 2003, pp. 297-303.

[143] F. Subhan, H. Hasbullah, A. Rozyyev, and S. T. Bakhsh, "Indoor positioning in Bluetooth networks using fingerprinting and lateration approach," in *Information Science and Applications (ICISA), 2011 International Conference on*, 2011, pp. 1-9.

[144] A. Baniukevic, D. Sabonis, C. S. Jensen, and L. Hua, "Improving Wi-Fi Based Indoor Positioning Using Bluetooth Add-Ons," in *Mobile Data Management (MDM), 2011 12th IEEE International Conference on*, 2011, pp. 246-255.

[145] P. Bauwens, "ULTRA-HIGH FREQUENCY," *British Medical Journal,* vol. 2, pp. 328-330, 1936.

[146] J. Werb and C. Lanzl, "Designing a positioning system for finding things and people indoors," *Spectrum, IEEE,* vol. 35, pp. 71-78, 1998.

[147] H. Nanda and L. Davis, "Probabilistic template based pedestrian detection in infrared videos," in *Intelligent Vehicle Symposium, 2002. IEEE*, 2002, pp. 15-20 vol.1.

[148] K. Briess, H. Jahn, E. Lorenz, D. Oertel, W. Skrbek, and B. Zhukov, "Fire recognition potential of the bi-spectral Infrared Detection (BIRD) satellite," *International Journal of Remote Sensing,* vol. 24, pp. 865-872, 2003/01/01 2003.

[149] E. P. G. Smith, L. T. Pham, G. M. Venzor, E. M. Norton, M. D. Newton, P. M. Goetz*, et al.*, "HgCdTe focal plane arrays for dual-color mid- and long-wavelength infrared detection," *Journal of Electronic Materials,* vol. 33, pp. 509-516, 2004/06/01 2004.

[150] B. U. Töreyin, Y. Dedeoğlu, U. Güdükbay, and A. E. Çetin, "Computer vision based method for real-time fire and flame detection," *Pattern Recognition Letters,* vol. 27, pp. 49-58, 1/1/ 2006.

[151] J. Han, L. Shao, D. Xu, and J. Shotton, "Enhanced computer vision with Microsoft Kinect sensor: a review," *IEEE Trans Cybern,* vol. 43, pp. 1318-34, Oct 2013.

[152] E. Hjelmås and B. K. Low, "Face Detection: A Survey," *Computer Vision and Image Understanding,* vol. 83, pp. 236-274, 9// 2001.

[153] Z. Zhengyou, "Microsoft Kinect Sensor and Its Effect," *MultiMedia, IEEE,* vol. 19, pp. 4-10, 2012.

[154] S. J. McKenna, S. Jabri, Z. Duric, A. Rosenfeld, and H. Wechsler, "Tracking Groups of People," *Computer Vision and Image Understanding,* vol. 80, pp. 42-56, 10// 2000.

[155] "The Weighting and Scoring Method " Retrieved December 10, 2013 from http://www.dfpni.gov.uk/eag-the-weighting-and-scoring-method.
[156] R. W. Frischholz and U. Dieckmann, "BiolD: a multimodal biometric identification system," *Computer,* vol. 33, pp. 64-68, 2000.
[157] C. H. Morimoto and M. Flickner, "Real-time multiple face detection using active illumination," in *Automatic Face and Gesture Recognition, 2000. Proceedings. Fourth IEEE International Conference on*, 2000, pp. 8-13.
[158] N. Oliver, A. Pentland, and F. Bérard, "LAFTER: a real-time face and lips tracker with facial expression recognition," *Pattern Recognition,* vol. 33, pp. 1369-1382, 8// 2000.
[159] W. Ce, S. Griebel, and M. Brandstein, "Robust automatic video-conferencing with multiple cameras and microphones," in *Multimedia and Expo, 2000. ICME 2000. 2000 IEEE International Conference on*, 2000, pp. 1585-1588 vol.3.
[160] P. Son Lam, A. Bouzerdoum, and D. Chai, "A novel skin color model in YCbCr color space and its application to human face detection," in *Image Processing. 2002. Proceedings. 2002 International Conference on*, 2002, pp. I-289-I-292 vol.1.
[161] T. Ahonen, A. Hadid, and M. Pietikainen, "Face Description with Local Binary Patterns: Application to Face Recognition," *Pattern Analysis and Machine Intelligence, IEEE Transactions on,* vol. 28, pp. 2037-2041, 2006.
[162] P. I. Wilson and J. Fernandez, "Facial feature detection using Haar classifiers," *J. Comput. Sci. Coll.,* vol. 21, pp. 127-133, 2006.
[163] G. C. Feng and P. C. Yuen, "Variance projection function and its application to eye detection for human face recognition," *Pattern Recognition Letters,* vol. 19, pp. 899-906, 7// 1998.
[164] H. A. Rowley, S. Baluja, and T. Kanade, "Neural network-based face detection," *Pattern Analysis and Machine Intelligence, IEEE Transactions on,* vol. 20, pp. 23-38, 1998.
[165] M. Jones and J. Rehg, "Statistical Color Models with Application to Skin Detection," *International Journal of Computer Vision,* vol. 46, pp. 81-96, 2002/01/01 2002.
[166] R. Kjeldsen and J. Kender, "Finding skin in color images," in *Automatic Face and Gesture Recognition, 1996., Proceedings of the Second International Conference on*, 1996, pp. 312-317.
[167] V. Vezhnevets, V. Sazonov, and A. Andreeva, "A survey on pixel-based skin color detection techniques," in *Proc. Graphicon*, 2003, pp. 85-92.
[168] H. Fleyeh, "Color detection and segmentation for road and traffic signs," in *Cybernetics and Intelligent Systems, 2004 IEEE Conference on*, 2004, pp. 809-814.
[169] T.-H. Chen, P.-H. Wu, and Y.-C. Chiou, "An early fire-detection method based on image processing," in *Image Processing, 2004. ICIP'04. 2004 International Conference on*, 2004, pp. 1707-1710.
[170] J. Torres-Sánchez, F. López-Granados, and J. M. Peña, "An automatic object-based method for optimal thresholding in UAV images: Application for vegetation detection in herbaceous crops," *Computers and Electronics in Agriculture,* vol. 114, pp. 43-52, 6// 2015.
[171] A. Mogelmose, M. M. Trivedi, and T. B. Moeslund, "Vision-Based Traffic Sign Detection and Analysis for Intelligent Driver Assistance Systems: Perspectives and Survey," *Intelligent Transportation Systems, IEEE Transactions on,* vol. 13, pp. 1484-1497, 2012.
[172] P. Doliotis, A. Stefan, C. McMurrough, D. Eckhard, and V. Athitsos, "Comparing gesture recognition accuracy using color and depth information," presented at the Proceedings of the 4th International Conference on PErvasive Technologies Related to Assistive Environments, Heraklion, Crete, Greece, 2011.
[173] http://sourceforge.net/projects/opencvlibrary/.
[174] http://opencvblobslib.github.io/opencvblobslib/.
[175] https://www.microsoft.com/en-us/kinectforwindows/meetkinect/default.aspx.
[176] http://self.gutenberg.org/articles/Xbox_Kinect.
[177] R. Knies, "Academics, Enthusiasts to Get Kinect SDK," February 21, 2011.

[178] http://blogs.msdn.com/b/kinectforwindows/archive/2012/01/09/kinect-for-windows-commercial-program-announced.aspx.
[179] http://latimesblogs.latimes.com/technology/2009/06/microsofte3.html.
[180] http://www2.technologyreview.com/tr50/primesense/.
[181] http://venturebeat.com/2009/09/05/how-many-vendors-does-it-take-to-make-microsofts-project-natal-game-control-system/.
[182] M. B. Wilson, Matt "Testing Project Natal: We Touched the Intangible," June 3, 2009.
[183] Z. Ren, J. Meng, J. Yuan, and Z. Zhang, "Robust hand gesture recognition with kinect sensor," presented at the Proceedings of the 19th ACM international conference on Multimedia, Scottsdale, Arizona, USA, 2011.
[184] Z. Ren, J. Yuan, and Z. Zhang, "Robust hand gesture recognition based on finger-earth mover's distance with a commodity depth camera," presented at the Proceedings of the 19th ACM international conference on Multimedia, Scottsdale, Arizona, USA, 2011.
[185] S. Gasparrini, E. Cippitelli, S. Spinsante, and E. Gambi, "A Depth-Based Fall Detection System Using a Kinect® Sensor," *Sensors,* vol. 14, pp. 2756-2775, 2014.
[186] K. Khoshelham and S. O. Elberink, "Accuracy and resolution of kinect depth data for indoor mapping applications," *Sensors,* vol. 12, pp. 1437-1454, 2012.
[187] R. Dubey, B. Ni, and P. Moulin, "A Depth Camera Based Fall Recognition System for the Elderly," in *Image Analysis and Recognition*. vol. 7325, A. Campilho and M. Kamel, Eds., ed: Springer Berlin Heidelberg, 2012, pp. 106-113.
[188] https://www.google.co.nz/search?q=Kinect&rlz=1C1CHMO_enNZ542NZ542&es_sm=122&biw=1920&bih=895&source=lnms&tbm=isch&sa=X&ved=0CAcQ_AUoAmoVChMI6YnPvp_zxwIVAxmmCh0aFAnd#tbm=isch&q=Kinect+for+windows&imgrc=TCzw_RVT1rF-MM%3A.
[189] N. Wilson, D. G. Russell, B. Wilson, F. New Zealand. Hillary Commission for Sport, Leisure, U. o. O. L. i. N. Z. Activity*, et al.*, *Size and Shape of New Zealanders: New Zealand Norms for Anthropometric Data*: Life in New Zealand Activity & Health Research Unit, University of Otago, 1993.
[190] https://www.visualstudio.com/downloads/download-visual-studio-vs.
[191] https://msdn.microsoft.com/en-nz/library/dn799271.aspx.
[192] R. Laganiere. (2011). *OpenCV 2 Computer Vision Application Programming Cookbook (1 ed.)*. Available: http://canterbury.eblib.com.au/patron/FullRecord.aspx?p=950571
[193] S. Emami and K. Levgen. (2012). *Mastering OpenCV with Practical Computer Vision Projects*. Available: http://canterbury.eblib.com.au/patron/FullRecord.aspx?p=1108328
[194] G. Bradski and A. Kaehler. (2008). *Learning OpenCV*. Available: http://canterbury.eblib.com.au/patron/FullRecord.aspx?p=540387
[195] S. Falahati, *Openni Cookbook*: Packt Publishing, 2013.
[196] http://openni.ru/index.html.
[197] https://code.google.com/p/kinect-mssdk-openni-bridge/.
[198] I. Pachoulakis and K. Kapetanakis, "Augmented reality platforms for virtual fitting rooms."
[199] https://github.com/OpenNI/OpenNI/blob/master/Documentation/OpenNI_UserGuide.pdf.
[200] http://opencv.org/about.html.
[201] https://dev.windows.com/en-us/kinect.
[202] http://structure.io/openni.
[203] V. S. Amos Gilat, "Numerical methods for engineers and scientists : an introduction with applications using MATLAB," 2011.
[204] L. V. Fausett., "Applied numerical analysis using MATLAB " 2008.
[205] G. W. Recktenwald., "Numerical methods with MATLAB : implementations and applications " 2000.
[206] G. R. P. Lindfield, John E.T, "Numerical Methods Using MATLAB," 2012.

[207] N. J. H. Desmond J. Higham, "MATLAB guide " 2000.
[208] Knaus, "APACHE-acute physiology and chronic health evaluation: a physiologically based classification system," *Critical Care Medicine,* vol. 9, pp. 591-597, 1981.
[209] Knaus, "APACHE II: A severity of disease classification system," *Critical Care Medicine,* vol. 13, pp. 818-829, 1985.
[210] Hamahata, "APACHE III, unlike APACHE II, predicts posthepatectomy mortality in patients with biliary tract carcinoma," *Critical Care Medicine,* vol. 26, pp. 1671-1676, 1998.
[211] J.-R. L. GALL, P. LOIRAT, A. ALPEROVITCH, P. GLASER, C. GRANTHIL, D. MATHIEU*, et al.*, "A simplified acute physiology score for ICU patients," *Critical Care Medicine,* vol. 12, pp. 975-977, 1984.
[212] J.-L. Vincent, A. de Mendonca, F. Cantraine, R. Moreno, J. Takala, P. M. Suter*, et al.*, "Use of the SOFA score to assess the incidence of organ dysfunction/failure in intensive care units: Results of a multicenter, prospective study," *Critical Care Medicine,* vol. 26, pp. 1793-1800, 1998.
[213] http://ethics.health.govt.nz/.
[214] G. Peng, A. Clark, C. Yeong Shiong, G. M. Shaw, S. Lei, and J. G. Chase, "Novel visualisation approach for Intensive Care Unit Clinical Activity monitoring," in *Industrial Electronics and Applications (ICIEA), 2014 IEEE 9th Conference on*, 2014, pp. 83-88.
[215] http://www.cdhb.health.nz/Hospitals-Services/Maori-Health/Te-Komiti-Whakarite/Pages/default.aspx.
[216] H. Lundgrén-Laine and T. Suominen, "Nursing intensity and patient classification at an adult intensive care unit (ICU)," *Intensive and Critical Care Nursing,* vol. 23, pp. 97-103, 4// 2007.
[217] K. H. Zou, K. Tuncali, and S. G. Silverman, "Correlation and simple linear regression 1," *Radiology,* vol. 227, pp. 617-628, 2003.
[218] J. M. Bland and D. Altman, "Statistical methods for assessing agreement between two methods of clinical measurement," *The Lancet,* vol. 327, pp. 307-310, 1986.
[219] K. Dewitte, C. Fierens, D. Stöckl, and L. M. Thienpont, "Application of the Bland–Altman plot for interpretation of method-comparison studies: a critical investigation of its practice," *Clinical Chemistry,* vol. 48, pp. 799-801, 2002.
[220] H. A. DeGroot, "Patient Classification Systems and Staffing," *Journal of Nursing Administration,* vol. 24, pp. 43-51, 1994.
[221] H. A. DeGroot, "Patient Classification Systems and Staffing: Part 2, Practice and Process," *Journal of Nursing Administration,* vol. 24, pp. 17-23, 1994.
[222] W. A. Knaus, J. E. Zimmerman, D. P. Wagner, E. A. Draper, and D. E. Lawrence, "APACHE-acute physiology and chronic health evaluation: a physiologically based classification system," *Critical Care Medicine,* vol. 9, pp. 591-597, 1981.
[223] W. A. KNAUS, E. A. DRAPER, D. P. WAGNER, and J. E. ZIMMERMAN, "APACHE II: A severity of disease classification system," *Critical Care Medicine,* vol. 13, pp. 818-829, 1985.
[224] J. R. Le Gall, S. Lemeshow, and F. Saulnier, "A new Simplified Acute Physiology Score (SAPS II) based on a European/North American multicenter study," *JAMA,* vol. 270, pp. 2957-63, Dec 22-29 1993.
[225] E. Castillo-Lorente, R. Rivera-Fernandez, M. Rodriguez-Elvira, and G. Vazquez-Mata, "Tiss 76 and Tiss 28: correlation of two therapeutic activity indices on a Spanish multicenter ICU database," *Intensive Care Medicine,* vol. 26, pp. 57-61, 2000.
[226] L. C. MION and J. D. FRENGLEY, "The impact of patients' severity of illness and age on nursing workload," *Nursing management,* vol. 19, pp. 26-37, 1988.
[227] W. W. Y. Kwok, J. P. C. Chau, L. P. Le Low, and D. R. Thompson, "The reliability and validity of the therapeutic activity index," *Journal of Critical Care,* vol. 20, pp. 257-263, 2005.
[228] K. L. Soeken and P. A. Prescott, "Patient intensity for nursing index: the measurement model," *Res Nurs Health,* vol. 14, pp. 297-304, 1991.

[229] P. Kiekkas, H. Brokalaki, E. Manolis, A. Samios, C. Skartsani, and G. Baltopoulos, "Patient severity as an indicator of nursing workload in the intensive care unit," *Nursing in Critical Care,* vol. 12, pp. 34-41, 2007.
[230] S. R. Edwardson and P. B. Giovannetti, "Nursing workload measurement systems," *Annual review of nursing research,* vol. 12, pp. 95-95, 1994.
[231] R. Endacott and A. Chellel, "Nursing dependency scoring: measuring the total workload," *Nursing standard (Royal College of Nursing (Great Britain): 1987),* vol. 10, pp. 39-42, 1996.
[232] R. Oye and P. Bellamy, "Patterns of resource consumption in medical intensive care," *CHEST Journal,* vol. 99, pp. 685-689, 1991.
[233] W. A. Knaus, E. A. Draper, D. P. Wagner, and J. E. Zimmerman, "APACHE II: a severity of disease classification system," *Crit Care Med,* vol. 13, pp. 818-29, Oct 1985.
[234] Rogers, "Use of daily Acute Physiology and Chronic Health Evaluation (APACHE) II scores to predict individual patient survival rate," *Critical Care Medicine,* vol. 22, pp. 1402-1405, 1994.
[235] http://www.sfar.org/scores/apache2.php.
[236] W. A. Knaus, D. P. Wagner, E. A. Draper, J. E. Zimmerman, M. Bergner, P. G. Bastos*, et al.*, "THe apache iii prognostic system. risk prediction of hospital mortality for critically ill hospitalized adults," *CHEST Journal,* vol. 100, pp. 1619-1636, 1991.
[237] https://dl.dropboxusercontent.com/u/56739431/ApacheIII_RiskScoreCard_AZ.pdf.
[238] J. E. Zimmerman, "Acute Physiology and Chronic Health Evaluation (APACHE) IV: Hospital mortality assessment for today???s critically ill patients*," *Critical Care Medicine,* vol. 34, pp. 1297-1310, 2006.
[239] http://clincalc.com/IcuMortality/APACHEII.aspx.
[240] P. H. Metnitz, R. Moreno, E. Almeida, B. Jordan, P. Bauer, R. Campos*, et al.*, "SAPS 3—From evaluation of the patient to evaluation of the intensive care unit. Part 1: Objectives, methods and cohort description," *Intensive Care Medicine,* vol. 31, pp. 1336-1344, 2005/10/01 2005.
[241] R. P. Moreno, P. G. Metnitz, E. Almeida, B. Jordan, P. Bauer, R. A. Campos*, et al.*, "SAPS 3--From evaluation of the patient to evaluation of the intensive care unit. Part 2: Development of a prognostic model for hospital mortality at ICU admission," *Intensive Care Med,* vol. 31, pp. 1345-55, 2005.
[242] R. Rivera-Lopez, E. Aguiar-Alonso, C. Lopez-Caler, E. Castillo-Lorente, M. Garcia-Delgado, and M. Arias-Verdú, "Validation of SAPS-3 and APACHE III in Mediterranean area," *Acta Medica Mediterr,* vol. 30, pp. 183-89, 2014.
[243] http://clincalc.com/IcuMortality/SAPSII.aspx.
[244] J. L. Vincent, R. Moreno, J. Takala, S. Willatts, A. De Mendonca, H. Bruining*, et al.*, *The SOFA (Sepsis-related Organ Failure Assessment) score to describe organ dysfunction/failure. On behalf of the Working Group on Sepsis-Related Problems of the European Society of Intensive Care Medicine*: Intensive Care Med. 1996 Jul;22(7):707-10.
[245] R. Moreno, J. L. Vincent, R. Matos, A. Mendonca, F. Cantraine, L. Thijs*, et al.*, "The use of maximum SOFA score to quantify organ dysfunction/failure in intensive care. Results of a prospective, multicentre study. Working Group on Sepsis related Problems of the ESICM," *Intensive Care Med,* vol. 25, pp. 686-96, 1999.
[246] A. de Mendonca, J. L. Vincent, P. M. Suter, R. Moreno, N. M. Dearden, M. Antonelli*, et al.*, "Acute renal failure in the ICU: risk factors and outcome evaluated by the SOFA score," *Intensive Care Med,* vol. 26, pp. 915-21, 2000.
[247] F. L. Ferreira, D. P. Bota, A. Bross, C. Melot, and J. L. Vincent, "Serial evaluation of the SOFA score to predict outcome in critically ill patients," *JAMA,* vol. 286, pp. 1754-8, 2001.
[248] http://clincalc.com/IcuMortality/SOFA.aspx.
[249] L. C. Kisorio and P. Becker, "Validity and reliability of the simplified Therapeutic Intervention Scoring System in intensive care units of a public sector hospital in Johannesburg," *Southern African Journal of Critical Care,* vol. 25, 2009.

[250] E. Castillo-Lorente, R. Rivera-Fernandez, M. Rodriguez-Elvira, and G. Vazquez-Mata, "Tiss 76 and Tiss 28: correlation of two therapeutic activity indices on a Spanish multicenter ICU database," *Intensive Care Med,* vol. 26, pp. 57-61, 2000.

[251] A. Fortis, C. Mathas, M. Laskou, S. Kolias, and N. Maguina, "Therapeutic Intervention Scoring System-28 as a tool of post ICU outcome prognosis and prevention," *Minerva Anestesiol,* vol. 70, pp. 71-81, 2004.

[252] D. J. CULLEN, A. R. NEMESKAL, and A. M. ZASLAVSKY, "Intermediate TISS: A new Therapeutic Intervention Scoring System for non-ICU patients," *Critical Care Medicine,* vol. 22, pp. 1406-1411, 1994.

[253] L. L. Y. Lee, K. L. Yeung, W. Y. L. Lo, Y. S. C. Lau, S. Y. H. Tang, and J. T. S. Chan, "Evaluation of a simplified therapeutic intervention scoring system (TISS-28) and the modified early warning score (MEWS) in predicting physiological deterioration during inter-facility transport," *Resuscitation,* vol. 76, pp. 47-51, 2008.

[254] N. Muehler, J. Oishi, M. Specht, F. Rissner, K. Reinhart, and Y. Sakr, "Serial measurement of Therapeutic Intervention Scoring System-28 (TISS-28) in a surgical intensive care unit," *Journal of Critical Care,* vol. 25, pp. 620-627, 12// 2010.

[255] G. Clermont, D. C. Angus, M. R. Pinsky, J. R. Lave, and W. T. Linde-Zwirble, "Measuring resource use in the ICU with computerized therapeutic intervention scoring system-based data," *CHEST Journal,* vol. 113, pp. 434-442, 1998.

[256] A. Junger, F. Brenck, B. Hartmann, J. Klasen, L. Quinzio, M. Benson*, et al.*, "Automatic calculation of the nine equivalents of nursing manpower use score (NEMS) using a patient data management system," *Intensive Care Medicine,* vol. 30, pp. 1487-1490, 2004/07/01 2004.

[257] P. G. H. Metnitz and K. Lenz, "Patient data management systems in intensive care — the situation in Europe," *Intensive Care Medicine,* vol. 21, pp. 703-715, 1995/09/01 1995.

[258] M. Urschitz, S. Lorenz, L. Unterasinger, P. Metnitz, K. Preyer, and C. Popow, "Three Years' Experience with a Patient Data Management System at a Neonatal Intensive Care Unit," *Journal of Clinical Monitoring and Computing,* vol. 14, pp. 119-125, 1998/02/01 1998.

[259] A. Perren, M. Previsdomini, I. Perren, and P. Merlani, "High accuracy of the nine equivalents of nursing manpower use score assessed by critical care nurses," *Swiss Medical Weekly,* vol. 5, p. 13555, 2012.

[260] F. J. Carmona-Monge, G. M. Rollán Rodríguez, C. Quirós Herranz, S. García Gómez, and D. Marín-Morales, "Evaluation of the nursing workload through the nine equivalents for nursing manpower use scale and the nursing activities score: A prospective correlation study," *Intensive and Critical Care Nursing,* vol. 29, pp. 228-233, 8// 2013.

[261] S. T. Canabarro, K. D. S. Velozo, O. R. Eidt, J. P. Piva, and P. C. R. Garcia, "Validação Concorrente de Escores de Enfermagem (NEMS e TISS-28) em terapia intensiva pediátrica," *Acta Paulista de Enfermagem,* vol. 26, pp. 123-129, 2013.

[262] S. K. Stafseth, D. Solms, and I. S. Bredal, "The characterisation of workloads and nursing staff allocation in intensive care units: A descriptive study using the Nursing Activities Score for the first time in Norway," *Intensive and Critical Care Nursing,* vol. 27, pp. 290-294, 10// 2011.

[263] A. Lucchini, C. De Felippis, S. Elli, L. Schifano, F. Rolla, F. Pegoraro*, et al.*, "Nursing Activities Score (NAS): 5 years of experience in the intensive care units of an Italian University hospital," *Intensive Crit Care Nurs,* vol. 30, pp. 152-8, 2014.

[264] L. A. Gonçalves, K. G. Padilha, and R. M. Cardoso Sousa, "Nursing activities score (NAS): A proposal for practical application in intensive care units," *Intensive and Critical Care Nursing,* vol. 23, pp. 355-361, 12// 2007.

[265] A. F. Queijo and K. G. Padilha, "Nursing Activities Score (NAS): cross-cultural adaptation and validation to Portuguese language," *Rev Esc Enferm USP,* vol. 43, pp. 1001-1008, 2009.

[266] W. Sermeus, L. Delesie, K. Van den Heede, L. Diya, and E. Lesaffre, "Measuring the intensity of nursing care: Making use of the Belgian Nursing Minimum Data Set," *International Journal of Nursing Studies,* vol. 45, pp. 1011-1021, 7// 2008.
[267] A. K. Rainio and A. E. Ohinmaa, "Assessment of nursing management and utilization of nursing resources with the RAFAELA patient classification system–case study from the general wards of one central hospital," *Journal of Clinical Nursing,* vol. 14, pp. 674-684, 2005.
[268] L. Fagerström, A. K. Rainio, A. Rauhala, and K. Nojonen, "Validation of a new method for patient classification, the Oulu Patient Classification," *Journal of Advanced Nursing,* vol. 31, pp. 481-490, 2000.
[269] http://www.radiometer.com/en/products/blood-gas-testing/abl90-flex-blood-gas-analyzer.
[270] http://www.anzics.com.au/Pages/CORE/data-tools.aspx.
[271] J. G. Chase, C. G. Pretty, L. Pfeifer, G. M. Shaw, J.-C. Preiser, A. J. Le Compte*, et al.*, "Organ failure and tight glycemic control in the SPRINT study," *Crit Care,* vol. 14, p. R154, 2010.
[272] H. Soliman, C. Melot, and J. L. Vincent, "Sedative and analgesic practice in the intensive care unit: the results of a European survey," *British journal of anaesthesia,* vol. 87, pp. 186-192, 2001.
[273] A. Weinbroum, V. Rudick, P. Sorkine, M. Freedman, E. Geller, and P. Halpern, "Midazolam versus propofol for long-term sedation in the ICU: a randomized prospective comparison," *Intensive Care Medicine,* vol. 23, pp. 1258-1263, 1997.
[274] R. R. Riker, Y. Shehabi, P. M. Bokesch, D. Ceraso, W. Wisemandle, F. Koura*, et al.*, "Dexmedetomidine vs midazolam for sedation of critically ill patients: a randomized trial," *JAMA,* vol. 301, pp. 489-499, 2009.
[275] M. Treggiari-Venzi, A. Borgeat, T. Fuchs-Buder, J.-P. Gachoud, and P. M. Suter, "Overnight sedation with midazolam or propofol in the ICU: effects on sleep quality, anxiety and depression," *Intensive Care Medicine,* vol. 22, pp. 1186-1190, 1996.
[276] C. N. Sessler, M. S. Gosnell, M. J. Grap, G. M. Brophy, P. V. O'Neal, K. A. Keane*, et al.*, "The Richmond Agitation–Sedation Scale," *American Journal of Respiratory and Critical Care Medicine,* vol. 166, pp. 1338-1344, 2002/11/15 2002.
[277] S. Stawicki, "ICU corner," *Crit Care Clin,* vol. 17, pp. 1-21, 2001.
[278] G. Teasdale and B. Jennett, "ASSESSMENT OF COMA AND IMPAIRED CONSCIOUSNESS: A Practical Scale," *The Lancet,* vol. 304, pp. 81-84, 7/13/ 1974.
[279] R. Heron, A. Davie, R. Gillies, and M. Courtney, "Interrater reliability of the Glasgow Coma Scale scoring among nurses in sub-specialties of critical care," *Aust Crit Care,* vol. 14, pp. 100-5, 2001.
[280] M. R. Gill, D. G. Reiley, and S. M. Green, "Interrater reliability of Glasgow Coma Scale scores in the emergency department," *Annals of Emergency Medicine,* vol. 43, pp. 215-223, 2// 2004.
[281] C. N. Sessler, M. S. Gosnell, M. J. Grap, G. M. Brophy, P. V. O'Neal, K. A. Keane*, et al.*, "The Richmond Agitation–Sedation Scale: validity and reliability in adult intensive care unit patients," *American Journal of Respiratory and Critical Care Medicine,* vol. 166, pp. 1338-1344, 2002.
[282] E. W. Ely, B. Truman, A. Shintani, J. W. Thomason, A. P. Wheeler, S. Gordon*, et al.*, "Monitoring sedation status over time in ICU patients: reliability and validity of the Richmond Agitation-Sedation Scale (RASS)," *JAMA,* vol. 289, pp. 2983-91, 2003.
[283] E. Ely, B. Truman, A. Shintani, and et al., "Monitoring sedation status over time in icu patients: Reliability and validity of the richmond agitation-sedation scale (rass)," *JAMA,* vol. 289, pp. 2983-2991, 2003.
[284] R. R. Riker, J. T. Picard, and G. L. Fraser, "Prospective evaluation of the Sedation-Agitation Scale for adult critically ill patients," *Critical Care Medicine,* vol. 27, pp. 1325-1329, 1999.

[285] A. Turkmen, A. Altan, N. Turgut, S. Vatansever, and S. Gokkaya, "The correlation between the richmond agitation–sedation scale and bispectral index during dexmedetomidine sedation," *European Journal of Anaesthesiology,* vol. 23, pp. 300-304, 2006.

[286] B. A. Khan, O. Guzman, N. L. Campbell, T. Walroth, J. L. Tricker, S. L. Hui*, et al.*, "COmparison and agreement between the richmond agitation-sedation scale and the riker sedation-agitation scale in evaluating patients' eligibility for delirium assessment in the icu," *Chest,* vol. 142, pp. 48-54, 2012.

[287] D. J. Hellawell, D. F. Signorini, and B. Pentland, "Simple assessment of outcome after acute brain injury using the Glasgow Outcome Scale," *Scandinavian journal of rehabilitation medicine,* vol. 32, pp. 25-27, 2000/03// 2000.

[288] J. D. Kerby, P. A. MacLennan, J. N. Burton, G. J. McGwin, and L. W. I. Rue, "Agreement Between Prehospital and Emergency Department Glasgow Coma Scores," *Journal of Trauma and Acute Care Surgery,* vol. 63, pp. 1026-1031, 2007.

[289] P. Udekwu, S. Kromhout-Schiro, S. Vaslef, C. Baker, and D. Oller, "Glasgow Coma Scale Score, Mortality, and Functional Outcome in Head-Injured Patients," *Journal of Trauma and Acute Care Surgery,* vol. 56, pp. 1084-1089, 2004.

[290] M. Tallgren, M. BÄCklund, and M. Hynninen, "Accuracy of Sequential Organ Failure Assessment (SOFA) scoring in clinical practice," *Acta Anaesthesiologica Scandinavica,* vol. 53, pp. 39-45, 2009.

[291] D. G. T. Arts, N. F. de Keizer, M. B. Vroom, and E. de Jonge, "Reliability and accuracy of Sequential Organ Failure Assessment (SOFA) scoring," *Critical Care Medicine,* vol. 33, pp. 1988-1993, 2005.

[292] D. Zygun, L. Berthiaume, K. Laupland, J. Kortbeek, and C. Doig, "SOFA is superior to MOD score for the determination of non-neurologic organ dysfunction in patients with severe traumatic brain injury: a cohort study," *Critical Care,* vol. 10, p. R115, 2006.

[293] D. Gommers and J. Bakker, "Medications for analgesia and sedation in the intensive care unit: an overview," *Critical Care,* vol. 12, pp. S4-S4, 05/14 2008.

[294] S. A. Nasraway, Jr., "Use of sedative medications in the intensive care unit," *Semin Respir Crit Care Med,* vol. 22, pp. 165-74, 2001.

[295] F. Agogué, "Objective measurements of patient agitation in critical care using physiological signals and fuzzy systems," 2005.

[296] K. G. Padilha, R. M. de Sousa, A. F. Queijo, A. M. Mendes, and D. Reis Miranda, "Nursing Activities Score in the intensive care unit: analysis of the related factors," *Intensive Crit Care Nurs,* vol. 24, pp. 197-204, Jun 2008.

[297] D. P. Debergh, D. Myny, I. Van Herzeele, G. Van Maele, D. R. Miranda, and F. Colardyn, "Measuring the nursing workload per shift in the ICU," *Intensive Care Medicine,* vol. 38, pp. 1438-1444, 2012.

[298] L. A. Gonçalves and K. G. Padilha, "Fatores associados à carga de trabalho de enfermagem em Unidade de Terapia Intensiva," *Rev Esc Enferm USP,* vol. 41, pp. 645-52, 2007.

[299] J. T. Ciampone, L. A. Gonçalves, F. d. O. M. Maia, and K. G. Padilha, "Necessidades de cuidados de enfermagem e intervenções terapêuticas em Unidade de Terapia Intensiva: estudo comparativo entre pacientes idosos e não idosos," *Acta Paul Enferm,* vol. 19, pp. 28-35, 2006.

[300] E. Castillo-Lorente, R. Rivera-Fernandez, and G. Vazquez-Mata, "Limitation of therapeutic activity in elderly critically ill patients," *Critical Care Medicine,* vol. 25, pp. 1643-1648, 1997.

[301] K. Mahmood, K. Eldeirawi, and M. M. Wahidi, "Association of gender with outcomes in critically ill patients," *Crit Care,* vol. 16, p. R92, 2012.

[302] S. A. Al Harbi, H. M. Tamim, and Y. M. Arabi, "Association between statin therapy and outcomes in critically ill patients: a nested cohort study," *BMC Pharmacology and Toxicology,* vol. 11, p. 12, 2011.

[303] J. Shamian, B. Hagen, T.-W. Hu, and T. E. Fogarty, "The relationship between length of stay and required nursing care hours," *Journal of Nursing Administration,* vol. 24, pp. 52-58, 1994.
[304] J. S. Krinsley, "Association Between Hyperglycemia and Increased Hospital Mortality in a Heterogeneous Population of Critically Ill Patients," *Mayo Clinic Proceedings,* vol. 78, pp. 1471-1478, 12// 2003.
[305] D. Pittet, D. Tarara, and R. P. Wenzel, "Nosocomial bloodstream infection in critically iii patients: Excess length of stay, extra costs, and attributable mortality," *JAMA,* vol. 271, pp. 1598-1601, 1994.
[306] S. E. Cosgrove, Y. Qi, K. S. Kaye, S. Harbarth, A. W. Karchmer, and Y. Carmeli, "The Impact of Methicillin Resistance in Staphylococcus aureus Bacteremia on Patient Outcomes: Mortality, Length of Stay, and Hospital Charges," *Infection Control & Hospital Epidemiology,* vol. 26, pp. 166-174, 2005.
[307] R. Byrick and G. Caskennette, "Audit of critical care: aims, uses, costs and limitations of a Canadian system," *Canadian Journal of Anaesthesia,* vol. 39, pp. 260-269, 1992/03/01 1992.
[308] D. R. Miranda, D. W. Ryan, W. Schaufeli, and V. Fidler, *Organisation and management of intensive care: a prospective study in 12 European countries* vol. 29: Springer Science & Business Media, 2012.
[309] S. M. Bagshaw, C. George, and R. Bellomo, "Early acute kidney injury and sepsis: a multicentre evaluation," *Critical Care,* vol. 12, p. R47, 2008.
[310] P. P. Pandharipande, A. K. Shintani, H. E. Hagerman, P. J. St Jacques, T. W. Rice, N. W. Sanders*, et al.*, "Derivation and validation of SpO2/FiO2 ratio to impute for PaO2/FiO2 ratio in the respiratory component of the Sequential Organ Failure Assessment (SOFA) Score," *Critical Care Medicine,* vol. 37, p. 1317, 2009.
[311] R. P. Dellinger, M. M. Levy, A. Rhodes, D. Annane, H. Gerlach, S. M. Opal*, et al.*, "Surviving Sepsis Campaign: international guidelines for management of severe sepsis and septic shock, 2012," *Intensive Care Medicine,* vol. 39, pp. 165-228, 2013.
[312] A. Viallon, S. Guyomarc'h, O. Marjollet, C. Berger, A. Carricajo, F. Robert*, et al.*, "Can emergency physicians identify a high mortality subgroup of patients with sepsis: role of procalcitonin," *European Journal of Emergency Medicine,* vol. 15, pp. 26-33, 2008.
[313] G. A. Wanner, M. Keel, U. Steckholzer, W. Beier, R. Stocker, and W. Ertel, "Relationship between procalcitonin plasma levels and severity of injury, sepsis, organ failure, and mortality in injured patients," *Critical Care Medicine,* vol. 28, pp. 950-957, 2000.
[314] P. J. Pronovost, D. Dang, T. Dorman, M. W. Jenckes, E. Garrett, and E. B. Bass, "ICU nurse to patient ratio greater than 1 to 2 associated with an increased risk of complications in abdominal aortic surgery patients," *Critical Care Medicine,* vol. 27, pp. A27-A27, Dec 1999.
[315] R. K. Amaravadi, J. B. Dimick, P. J. Pronovost, and P. A. Lipsett, "ICU nurse-to-patient ratio is associated with complications and resource use after esophagectomy," *Intensive Care Med,* vol. 26, pp. 1857-62, 2000.
[316] K. Hurst, A. Smith, A. Casey, K. Fenton, H. Scholefield, and S. Smith, "Calculating staffing reguirements: Keith Hurst and colleagues describe how they devised a method for calculating the number of nurses needed to care for different patients with different levels of dependency," *Nursing management,* vol. 15, pp. 26-34, 2008.
[317] J. H. Kim, S.-K. Hong, K. C. Kim, M.-G. Lee, K. M. Lee, S. S. Jung*, et al.*, "Influence of full-time intensivist and the nurse-to-patient ratio on the implementation of severe sepsis bundles in Korean intensive care units," *Journal of Critical Care,* vol. 27, pp. 414. e11-414. e21, 2012.
[318] D. Reis Miranda, R. Rivera-Fernández, and R. E. Nap, "Critical care medicine in the hospital: lessons from the EURICUS-studies," *Medicina Intensiva,* vol. 31, pp. 194-203, 5// 2007.
[319] A. O. Gallesio, "Resource Management and Audits in Intensive Care Medicine," in *Intensive and Critical Care Medicine*, A. Gullo and P. Lumb, Eds., ed: Springer Milan, 2005, pp. 55-69.

[320] X. J. Wang, G. D. Li, Z. L. Zhang, and Z. Li, "Design on Light Geodesic Instrument Semi-Physical Simulation Training System Based on Virtual Scene," in *Advanced Materials Research*, 2014, pp. 1517-1521.

[321] C. Liying, S. Qi, S. Han, C. Yang, and Z. Shuying, "Design and implementation of human-robot interactive demonstration system based on Kinect," in *Control and Decision Conference (CCDC), 2012 24th Chinese*, 2012, pp. 971-975.

[322] M. Livingston, J. Sebastian, Z. Ai, and J. W. Decker, "Performance measurements for the Microsoft Kinect skeleton," in *Virtual Reality Short Papers and Posters (VRW), 2012 IEEE*, 2012, pp. 119-120.

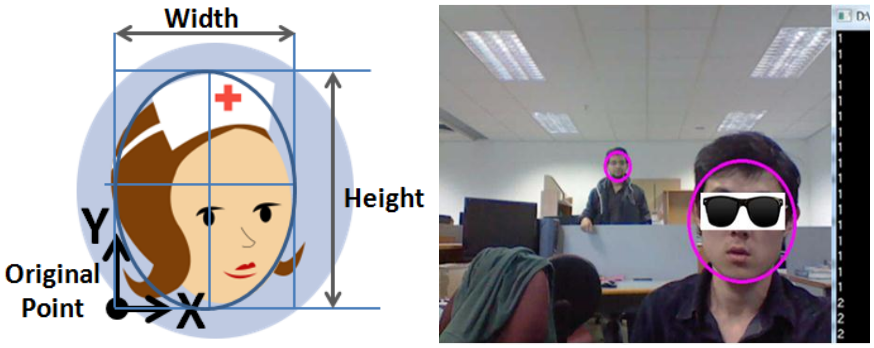
[323] P. Breuer, C. Eckes, and S. Müller, "Hand Gesture Recognition with a Novel IR Time-of-Flight Range Camera–A Pilot Study," in *Computer Vision/Computer Graphics Collaboration Techniques*. vol. 4418, A. Gagalowicz and W. Philips, Eds., ed: Springer Berlin Heidelberg, 2007, pp. 247-260.

[324] http://docs.opencv.org/doc/tutorials/objdetect/cascade_classifier/cascade_classifier.html.

Appendix

Appendix 2.1: Algorithm of human face detection, written in C++ 2010

To implement Facial detection, in this particular application, system implements OpenCV library [100, 173]. An inbuilt class 'CascadeClassifier' [324] is developed for facial detection. The identification program can be extended to identify different persons by comparing facial features. First, system extracts image frames from webcam at 30Hz frequency. Then, system processes each frame, finding all faces on each frame by using function '`detectMultiScale`', calculating the original point, width, and height of face. Then, system creates an ellipse with the centre at (original point + half width, original point + half height) and axis of width and height to show the locations of all faces being detected, as shown in figure below:



(Left): Face detection algorithm. After system detects human face feature, it calculate the original point, width and height. Draw an ellipse with the centre at (original point + half width, original point + half height) and axis of width and height.

(Right): Face recognition of 2 people with relative ellipse to show face location. The number of faces is shown in a real-time based 'cmd.exe' window.

The location of each face and the number of faces can be recorded in real-time. System can also detect eyes and draw the positions by using 'CascadeClassifier' class, which is similar as face detection. The entire procedure is demonstrated in following code:

```
#include "opencv2/objdetect/objdetect.hpp"
#include "opencv2/highgui/highgui.hpp"
#include "opencv2/imgproc/imgproc.hpp"
#include <iostream>
#include <stdio.h>
#include <opencv/cv.h>
#include <opencv/highgui.h>
#include <opencv/cxcore.h>
#include <time.h>
#include "Threshold.h"
using namespace std;
using namespace cv;
//Face Detect
CascadeClassifier face_cascade;
CascadeClassifier eyes_cascade;
std::vector<Rect> faces;
std::vector<Rect> eyes;
Mat frame_gray;
void detectFace(cv::Mat frame);
time_t lastSavedTime;
FILE *pFile;
IplImage* GetThresholdedImage(IplImage* img);
int main( int argc, const char** argv )
{
	if( !face_cascade.load( "./haarcascade_frontalface_alt.xml" ) ){ printf("--
(!)Error loading\n"); return -1;};
if( !eyes_cascade.load( "./haarcascade_eye_tree_eyeglasses.xml" ) ){ printf("--
(!)Error loading\n"); return -1; };
CvCapture* capture = cvCaptureFromCAM( 0 ); // connect to a camera
	pFile =fopen ("log.csv","w");
	lastSavedTime = time(NULL);

	while (cvWaitKey(10) < 0)
	{
		IplImage* frame = cvQueryFrame( capture ); // get the next frame of
video
		detectFace(frame);
	}
	fclose (pFile);
	cvReleaseCapture( &capture );
	cvDestroyWindow("faces");
	return 0;
}

 void detectFace(cv::Mat frame) {
	 face_cascade.detectMultiScale( frame, faces, 1.1, 2, 0|CV_HAAR_SCALE_IMAGE,
Size(30, 30) ); // Detect faces
	 Mat frameClone = frame.clone();
		for( int i = 0; i < faces.size(); i++ ) // for each face found
		{
			Point center( faces[i].x + faces[i].width*0.5, faces[i].y +
faces[i].height*0.5 ); // location of this face
			ellipse( frameClone, center, Size( faces[i].width*0.5,
faces[i].height*0.5), 0, 0, 360, Scalar( 255, 0, 255 ), 4, 8, 0 ); // draw ellipse
around this face
```

```
            }

            imshow( "faces", frameClone);
}
```

Appendix 2.2: Algorithm of color detection, written in C++ 2010

System implements 'OpenCV' [100, 173] and 'OpenCVBlobsLib' libraries [174] for image processing. First, a stream of 640×480 pixels RGB video frames is collected by webcam at 30Hz frequency. Each pixel from RGB image contains 3 channels, saving 'Red', 'Green', and 'Blue' values. Each channel utilized 8-bits space, saving values from 0~255. Second, RGB image is transferred to HSV (hue, saturation and value) image. HSV image also uses 3 channels, storing 'Hue', 'Saturation', and 'Value' information. Using HSV frames, it is much easier to filter a specific color, as color information is saved in 'Hue' channel. For this application, nurses dress blue uniform, and blue can be filtered by setting up color range 'cvScalar (110,100,000)' to 'cvScalar (120, 255, 255)'. Third, system creates a 640×480 pixels Black & White (B&W) image, each pixel contains a 1-channel, 8-bits information, saving values from 0~255. All the pixels filtered in HSV image generates a 'White' pixel (value 255) in B&W image, all the rest are set as 'Black'. At last, for the B&W image, system separates those human size blobs, ignoring noise (blobs too small), creating the centre and boundary of each blob, and recording each centre into a 'txt' file. Figure 2.2 shows an example where a test candidate simulates nursing staff by wearing a blue uniform. Using the designated color filtering, the uniform is highlighted. The entire procedure is demonstrated in following code:

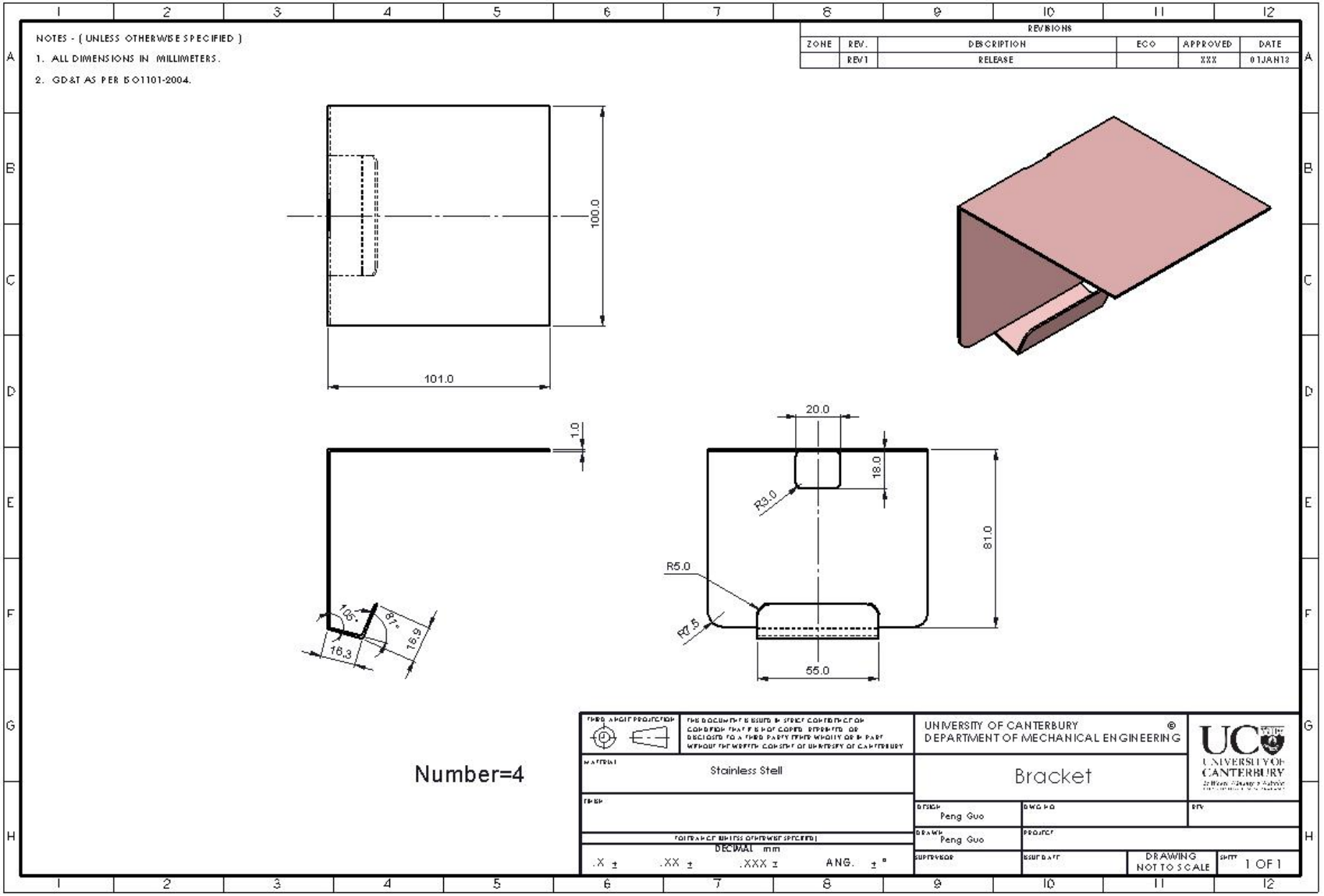
```
#include "opencv2/objdetect/objdetect.hpp"
#include "opencv2/highgui/highgui.hpp"
#include "opencv2/imgproc/imgproc.hpp"
#include <iostream>
#include <stdio.h>
#include <opencv/cv.h>
#include <opencv/highgui.h>
#include <BlobResult.h>
#include <opencv/cxcore.h>
#include <time.h>
using namespace std;
using namespace cv;
Mat frame_gray;
void detectFace(cv::Mat frame);

//Blob Detect
CBlobResult blobs;
CBlob *currentBlob;
```

```
time_t lastSavedTime;
FILE *pFile;
void blobDetect(IplImage *frame,FILE *pFile,time_t lastSavedTime)  ;
time_t WriteTime(FILE *pFile,time_t lastSavedTime,int num_blobs,CvPoint bottom);
IplImage* GetThresholdedImage(IplImage* img);

 int main( int argc, const char** argv )
{
	CvCapture* capture = cvCaptureFromCAM( 0 ); // connect to a camera
	pFile =fopen ("log.csv","w");
	lastSavedTime = time(NULL);
	while (cvWaitKey(10) < 0)
	{
		IplImage* frame = cvQueryFrame( capture ); // get the next frame of
video
		blobDetect(frame,pFile,lastSavedTime);
	}
	fclose (pFile);
	cvReleaseCapture( &capture );
	cvDestroyWindow("faces");
	return 0;
}

void blobDetect(IplImage *frame,FILE *pFile,time_t &lastSavedTime)
{
	 // Holds the yellow thresholded image (yellow = white, rest = black)
	 IplImage* imgYellowThresh = GetThresholdedImage(frame);
		// Find the white blobs in the B&W image
	   blobs = CBlobResult( imgYellowThresh, NULL, 0 );
	   // Exclude all white blobs smaller than the given value (80)  The bigger the
last parameter, the bigger the blobs need to be for inclusion
	   blobs.Filter( blobs,
				B_EXCLUDE,
				CBlobGetArea(),
				B_LESS,2000);
	   //// Get the number of blobs discovered
	   int num_blobs = blobs.GetNumBlobs();
	   //time_t currentTime; currentTime = time(NULL);
	   for ( int i = 0; i < num_blobs; i++ )
	   {
		currentBlob = blobs.GetBlob( i );
		   double m00 = currentBlob->Moment(0, 0);
		   double m10 = currentBlob->Moment(1, 0);
		   double m01 = currentBlob->Moment(0, 1);
		CvPoint centre;
		   centre.x = (int) m10/m00;
// calculate the x,y centre of motion
		   centre.y = (int) m01/m00;
		   CvRect r = currentBlob->GetBoundingBox();
		   cvRectangleR   ( imgYellowThresh, r, CV_RGB(255,255,255)); //
mark the rectangular of motion
		   cvRectangleR   (imgYellowThresh, r, CV_RGB(255,255,255));
		   //draw the bottom of the blob
		   CvPoint bottom;
		   bottom.x=(int)centre.x;
		   bottom.y=(int)centre.y+r.height/2;
		   cvCircle   ( imgYellowThresh, bottom, 8,
CV_RGB(255,255,255),6,10,0); // mark the centre of motion
		   cvCircle   ( imgYellowThresh, bottom, 8, CV_RGB(255,255,255));
		   //write the bottom point into database
```

```
                    lastSavedTime=WriteTime(pFile,lastSavedTime,num_blobs,bottom);
                    cvShowImage("Depth Image B/W(With the centre point)",
imgYellowThresh);
          }
        // Release the thresholded image... we need no memory leaks.. please
        cvReleaseImage(&imgYellowThresh);
}
 IplImage* GetThresholdedImage(IplImage* img)
{
    // Convert the image into an HSV image
    IplImage* imgHSV = cvCreateImage(cvGetSize(img), 8, 3);
    cvCvtColor(img, imgHSV, CV_BGR2HSV);
    IplImage* imgThreshed = cvCreateImage(cvGetSize(img), 8, 1);
    // Values 20,100,100 to 30,255,255 working perfect for yellow at around 6pm
    cvInRangeS(imgHSV, cvScalar(110,100,000), cvScalar(120, 255, 255), imgThreshed);
    cvReleaseImage(&imgHSV);
    return imgThreshed;
}

time_t WriteTime(FILE *pFile,time_t *lastSavedTime,int num_blobs,CvPoint bottom)
{
              time_t currentTime; currentTime = time(NULL);
              //write data in every 5 seconds
              if (currentTime-(*lastSavedTime)>4) {
                 struct tm *currentPrint;
                 currentPrint = localtime(&currentTime);
                 fprintf( pFile, "%d",currentPrint->tm_year+1900);
                 if (currentPrint->tm_mon<9)
                        fprintf( pFile, "0%d",currentPrint->tm_mon+1);
                 else
                        fprintf( pFile, "%d",currentPrint->tm_mon+1);
                 if (currentPrint->tm_mday<10)
                        fprintf( pFile, "0%d",currentPrint->tm_mday);
                 else
                        fprintf( pFile, "%d",currentPrint->tm_mday);
                 if (currentPrint->tm_hour<10)
                        fprintf( pFile, "0%d",currentPrint->tm_hour);
                 else
                        fprintf( pFile, "%d",currentPrint->tm_hour);
                 if (currentPrint->tm_min<10)
                        fprintf( pFile, "0%d",currentPrint->tm_min);
                 else
                        fprintf( pFile, "%d",currentPrint->tm_min);
                 if (currentPrint->tm_sec<10)
                        fprintf( pFile, "0%d ",currentPrint->tm_sec);
                 else
                        fprintf( pFile, "%d ",currentPrint->tm_sec);
                 for ( int i = 0; i < num_blobs; i++ )
                 {
                  currentBlob = blobs.GetBlob( i );
                     double m00 = currentBlob->Moment(0, 0);
                     double m10 = currentBlob->Moment(1, 0);
                     double m01 = currentBlob->Moment(0, 1);
                  CvPoint centre;
                     centre.x = (int) m10/m00;
// calculate the x,y centre of motion
                     centre.y = (int) m01/m00;
                            if ((centre.x > 0) && (centre.y > 0))
                                   fprintf( pFile, "x%d=%d, y%d=%d ",
i,bottom.x,i,bottom.y);
                 }
                 fprintf( pFile,"\n");
```

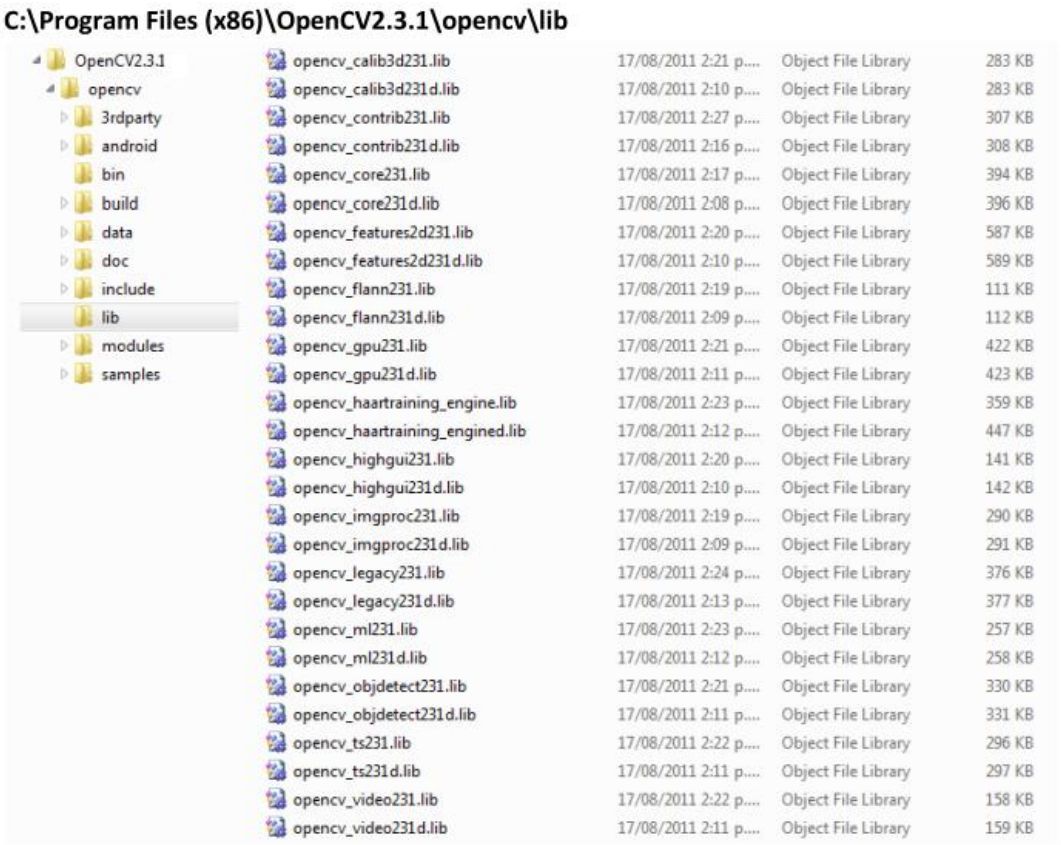
```
                lastSavedTime = currentTime;
                return(lastSavedTime);
        }

}
```

Appendix 3.1: Bracket dimensions



Appendix 3.2: Steps to setup OpenCV library:

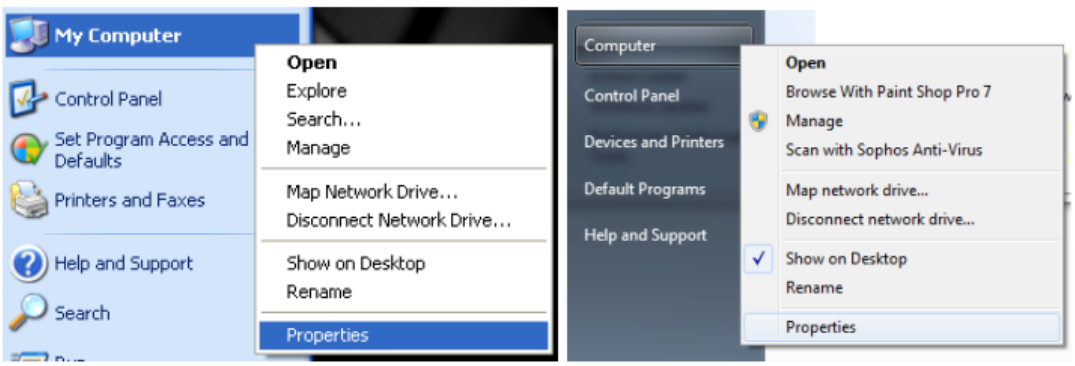
Step 1: Install ‘OpenCV’ under ‘C:\Program Files (x86)’. All the libraries should be under ‘C:\Program Files (x86)\OpenCV2.3.1\opencv\lib’:



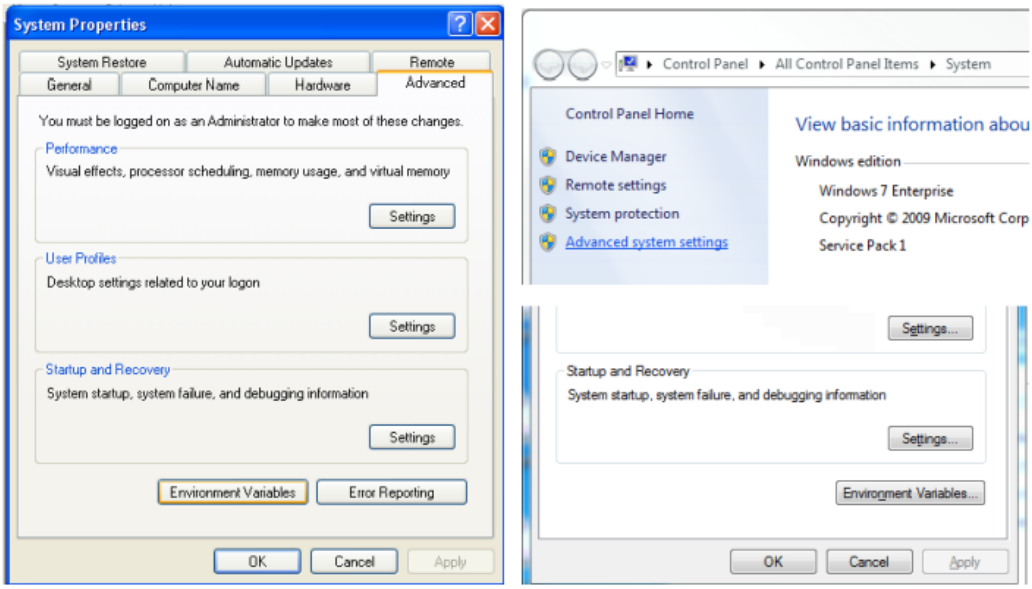
Step 2: Setup environmental variables:

To make it easier to run code on other machines, system uses a couple of environment variables to link to the path where OpenCV is installed.

Click on the Start Menu and right click on Computer (Windows 7)

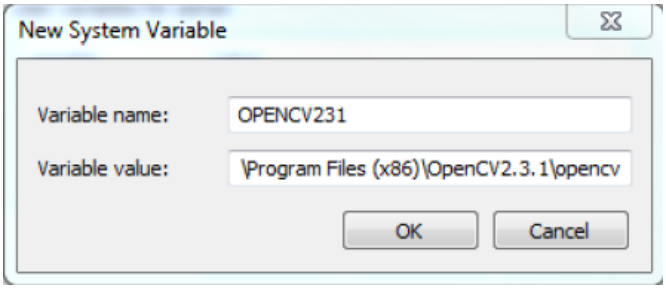


In the window which pops up, click on the Advanced tab, then Environment Variables (Windows XP), or Advanced System Settings then Environment Variables (Windows 7).



In the “Environment Variables” window which pops up, under “System Variables”, click on New. For the Variable Name put in OpenCV231 and for Variable Value put in the directory where OpenCV installed, including the opencv inner folder, eg.

C:\Program Files (x86)\OpenCV2.3.1\opencv

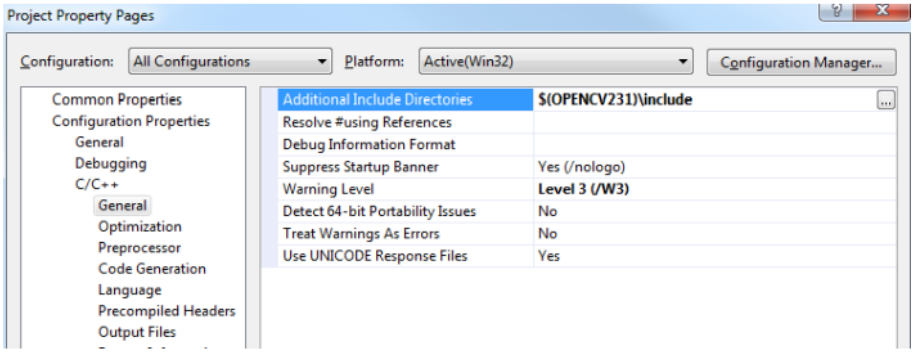


Next, scroll down the System Variables to find the Path variable. Click on it, then click edit. Scroll to the end of the variable value, and add a semi-colon, then the path above, but with bin on the end, eg: ‘C:\Windows\System32’ becomes ‘C:\Windows\System32;C:\Program Files (x86)\OpenCV2.3.1\opencv\bin’

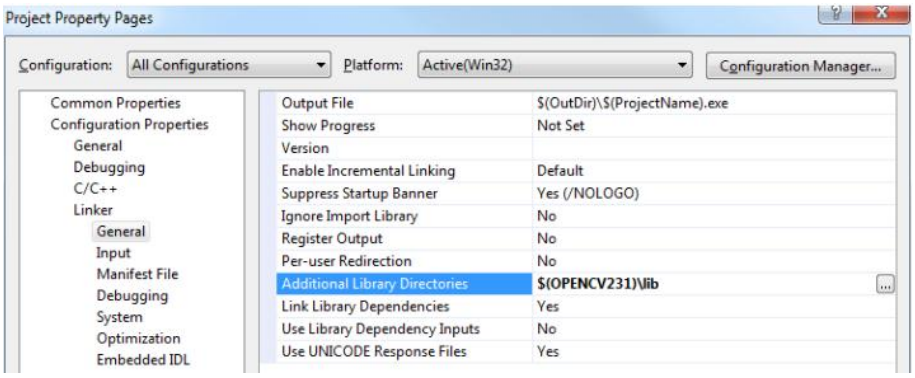
After this step, it needs to restart computer to make sure Windows loads in the new variables.

Setup 3: Development Environment Setting:

All that is left to do now is to set up your Visual Studio environment. Create a new Visual Studio project. Click on the "Project" toolbar, and then go down to "Project Properties" (Visual Studio 2008) or "Properties" (Visual Studio 2010). Open Configuration Properties, Then C/C++, then click on General. Under "Additional Include Directories", write "$(OPENCV231)\include".

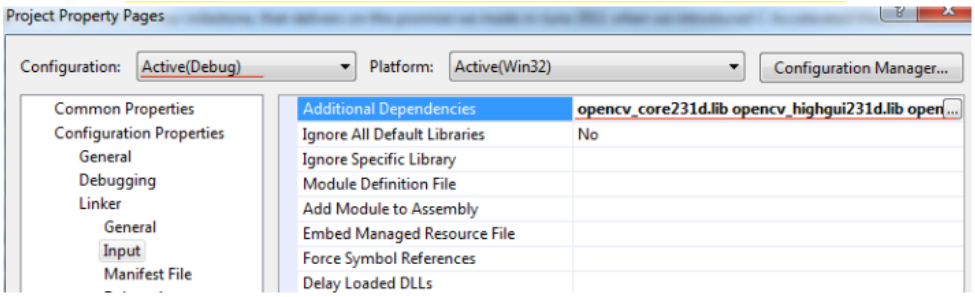


Open Linker, then General, and under "Additional Library Directories", write "$(OPENCV231)\lib".



System needs ‘opencv_core231’, ‘opencv_highgui231’ and ‘opencv_imgproc231’. These should be added under Linker, Input, “Additional Directories”. In the Debug Configuration (in the drop down box at the top left of the window), enter the following:

opencv_core231d.lib opencv_highgui231d.lib opencv_imgproc231d.lib



Appendix 3.3: Algorithm of blob detection, written in C++ 2010

```
#include <XnOS.h>
#include <XnCppWrapper.h>
//OpenCV
#include <opencv/cv.h>
#include <opencv/highgui.h>
#include <BlobResult.h>
#include <opencv/cxcore.h>
#include <time.h>
#include <stdio.h>
#include <math.h>

using namespace std;
using namespace xn;

// ****** Defines ******
#define KINECT_XML_PATH "Data/SamplesConfig.xml"
//Create a mask of valid depth values
IplImage *createDepthMask(IplImage *depth_image);
double getBlobDistance(CBlob *blob1,CBlob *blob2);


typedef struct blobValue
{
    double mean;
    CvRect r;
       CvPoint centre;
}
blobValue;

int main(int argc, char* argv[])
{
    FILE *pFile = fopen ("log.csv","w");
    //Kinect Objects
    Context niContext;
    DepthGenerator niDepth;
    ImageGenerator niImage;

       // Create VideoWriter objects (uninitialised)
       cv::VideoWriter imageVideo;
       cv::VideoWriter depthVideo;
       bool areVideosInitialised = false;

    //Initialize Kinect
    EnumerationErrors errors;
    switch (XnStatus rc = niContext.InitFromXmlFile(KINECT_XML_PATH, &errors)) {
        case XN_STATUS_OK:
            break;
        case XN_STATUS_NO_NODE_PRESENT:
            XnChar strError[1024];    errors.ToString(strError, 1024);
            printf("%s\n", strError);
            return rc; break;
        default:
            printf("Open failed: %s\n", xnGetStatusString(rc));
            return rc;
    }

    //Extract the Image and Depth nodes from the Kinect Context
    niContext.FindExistingNode(XN_NODE_TYPE_DEPTH, niDepth);
    niContext.FindExistingNode(XN_NODE_TYPE_IMAGE, niImage);
```

```
    ////Align the depth image and colourImage
    niDepth.GetAlternativeViewPointCap().SetViewPoint(niImage);
    niDepth.GetMirrorCap().SetMirror(false);

    //The Maximum and Minimum Kinect Depth values (used for visualisation)
    //float kinectDepthMax = 1360, kinectDepthMin = 1060;
       float kinectDepthMax = 2860, kinectDepthMin = 1260;

       //set two variables: lastSavedTime anf running
    bool running = true;
       time_t lastSavedTime; lastSavedTime = time(NULL);

       //define the startTime
       time_t startTime; startTime = time(NULL);
       //Create time text and font
       char timeString[20];
       strftime(timeString, 20, "%Y-%m-%d %H:%M:%S", localtime(&startTime));
       CvFont font;
    cvInitFont(&font, CV_FONT_HERSHEY_SIMPLEX, 0.5, 0.5);

    //Circle starts from here.
    while (running) {
        if (XnStatus rc = niContext.WaitAnyUpdateAll() != XN_STATUS_OK) {
            printf("Read failed: %s\n", xnGetStatusString(rc));
            return rc;
        }
        // Update MetaData containers
        DepthMetaData niDepthMD; ImageMetaData niImageMD;
        niDepth.GetMetaData(niDepthMD); niImage.GetMetaData(niImageMD);

              //Create currentTime
              time_t currentTime; currentTime = time(NULL);
              strftime(timeString, 20, "%Y-%m-%d %H:%M:%S", localtime(&currentTime));

              // Initialise video containers now that the image dimensions are known
              if (!areVideosInitialised) {
            imageVideo.open("image.mpeg", CV_FOURCC('M','P','4','S'), 7.0,
cv::Size(niImageMD.XRes(), niImageMD.YRes()));
            depthVideo.open("depth.mpeg", CV_FOURCC('M','P','4','S'), 7.0,
cv::Size(niDepthMD.XRes(), niImageMD.YRes()));
                    areVideosInitialised = true;
              }

        // Extract Colour Image
        IplImage *colourImage = cvCreateImage(cvSize(niImageMD.XRes(),
niImageMD.YRes()), IPL_DEPTH_8U, 3);
        memcpy(colourImage->imageData, niImageMD.Data(), colourImage->imageSize);
              cvConvertImage(colourImage, colourImage, CV_CVTIMG_SWAP_RB);
        cvFlip(colourImage, colourImage, 1);
              cvRectangle(colourImage,
cvPoint(160,360),cvPoint(480,480),cvScalar(0,255,255), -1); //draw a rectangulor on
the image
              cvPutText(colourImage, timeString, cvPoint(440,20), &font,
cvScalar(0,0,255));
              cvShowImage("Colour Image", colourImage);

              // Save the colourImage to the output video file
              cv::Mat imageMat(colourImage, false);
              imageVideo << imageMat;

        // Extract Depth Image
```

```
        IplImage *depthImage = cvCreateImage(cvSize(niImageMD.XRes(),
niImageMD.YRes()), IPL_DEPTH_16U, 1);
        memcpy(depthImage->imageData, niDepthMD.Data(), depthImage->imageSize);
              //cvShowImage("Depth Image", depthImage);

        //Create a mask of the valid values for the depth image
        IplImage *depthImageMask = createDepthMask(depthImage);
        //cvShowImage("Depth Image Mask", depthImageMask);

        // Convert Depth Image into visible spectrum
        float scale = 255.0/(kinectDepthMax-kinectDepthMin), shift = -
kinectDepthMin*scale;
        IplImage *depthImageVisible = cvCreateImage(cvGetSize(depthImage),
IPL_DEPTH_8U, 1);
              cvSetZero(depthImageVisible);
        cvConvertScale(depthImage, depthImageVisible, scale, shift);
              cvSubRS(depthImageVisible, cvScalarAll(255), depthImageVisible,
depthImageMask);
        //cvShowImage("Depth Image Visible", depthImageVisible);
              ////////////////////////////////////////////////////////////////////////


          // define blobs and get blobs from depthImageVisible
              CBlobResult blobs;
              blobs = CBlobResult( depthImageVisible, NULL, 0 );
              //cout<<"number of blobs is"<<blobs->m_blobs.size;


          // Exclude all white blobs smaller than the given value (2000)
          // The bigger the last parameter, the bigger the blobs need
          // to be for inclusion
          blobs.Filter( blobs,
                                    B_EXCLUDE,
                                    CBlobGetArea(),
                                    B_LESS,1500);
          blobs.Filter( blobs,
                                    B_EXCLUDE,
                                    CBlobGetArea(),
                                    B_GREATER,30000);
          // Get the number of blobs discovered
          int num_blobs = blobs.GetNumBlobs();

          //give each blob a group index

          CBlob *currentBlob;
          CBlob *previousBlob;
          CBlobResult blobGroup[4];
          CBlobResult blobBrightest;//blobBrightest is set to save the brightest blob
in each group
          int num_blobGroup=1;
          if (num_blobs>0){
                //copy blobs[0] to blobGroup[0]
                blobGroup[0].AddBlob(blobs.GetBlob( 0 ));
                //for blobs[1]-blobs[num_blobs], compare each blob with the previous
ones, give each blob a group
                for ( int i = 1; i < num_blobs; i++ ){
                      currentBlob=blobs.GetBlob(i);
                      bool creatNewGroup=1;
                      //previousBlob=blobGroup[i-1].GetBlob(0);
                      //caculate the distance between each blob in blobs with the
first blob in ,then write each blob in blobs to blobGroup
```

```
                        for(int j=0;j<num_blobGroup;j++){
                                if
(getBlobDistance(currentBlob,blobGroup[j].GetBlob(0))<150){  //compare each blob with
the first blob in each blobGroup,set distance 120
                                        blobGroup[j].AddBlob(currentBlob);
                                        creatNewGroup=0;
                                }
                            }
                            if(creatNewGroup==1){
                                    num_blobGroup++;
                                    blobGroup[num_blobGroup-1].AddBlob(currentBlob);
                            }
                    }

                    //for each group,calculate which is the brightest blob and write it
into "blobBrightest".
                    for(int j=0;j<num_blobGroup;j++){
                            CBlob* brightestBlob;
                            brightestBlob=blobGroup[j].GetBlob(0);
                            int num_eachGroup=blobGroup[j].GetNumBlobs();
                            CvPoint brightestBlobCentre;
                            CvRect brightestBlobRect;
                            int brightestBlobMean;
                            double n00 = brightestBlob->Moment(0, 0);
                            double n10 = brightestBlob->Moment(1, 0);
                            double n01 = brightestBlob->Moment(0, 1);
                            brightestBlobCentre.x = (int) n10/n00;
// calculate the x,y centre of motion
                            brightestBlobCentre.y = (int) n01/n00;
                            brightestBlobRect= brightestBlob->GetBoundingBox();

                            brightestBlobMean = brightestBlob->Mean(depthImageVisible);
                            //compare each blob in that blobGroup with the first one, if
it's brighter than brightest one, replace it.
                            for(int k=1;k<num_eachGroup;k++){
                                    CvPoint currentBlobCentre;
                                    int currentBlobMean;
                                    CvRect currentBlobRect;
                                    currentBlob = blobs.GetBlob(k);
                                    double m00 = currentBlob->Moment(0, 0);
                                    double m10 = currentBlob->Moment(1, 0);
                                    double m01 = currentBlob->Moment(0, 1);
                                    currentBlobCentre.x = (int) m10/m00;
// calculate the x,y centre of motion
                                    currentBlobCentre.y = (int) m01/m00;
                                    currentBlobRect= currentBlob->GetBoundingBox();

                                    currentBlobMean = currentBlob-
>Mean(depthImageVisible);
                                    if (currentBlobMean>brightestBlobMean){
                                            brightestBlob=currentBlob;
                                    }
                            }
                            cvCircle   ( depthImageVisible, brightestBlobCentre, 8,
CV_RGB(0,0,0)); // mark the centre of motion
                        cvRectangleR   (depthImageVisible, brightestBlobRect,
CV_RGB(255,0,255));  // mark the rectangular of motion
                            cvPutText(depthImageVisible, timeString, cvPoint(440,20),
&font, cvScalar(255,255,255));//dispaly the current time
                        cvShowImage("depthImageVisible (With the centre
point)",depthImageVisible);//show depthImageVisible
                            blobBrightest.AddBlob(brightestBlob);
```

```
                }
                // Save the depthImageVisible to the output video file
                IplImage *depthImageVisible3Channels =
cvCreateImage(cvGetSize(depthImage), IPL_DEPTH_8U, 3);
                cvCvtColor(depthImageVisible, depthImageVisible3Channels,
CV_GRAY2BGR);
           cv::Mat depthMat(depthImageVisible3Channels, false);//convert to right
format
           depthVideo << depthMat;//save image
                cvReleaseImage(&depthImageVisible3Channels);
          }

                //Write the brightest blobs into pFile
                if (currentTime-lastSavedTime>0) {
                       cout<<"we are writing time!!!\n";
                       struct tm *currentPrint;
                       currentPrint = localtime(&currentTime);
                       //fprintf(pFile, "%d%02d%02d %02d%02d%02d ", currentPrint-
>tm_year+1900, currentPrint->tm_mon+1,
                                //currentPrint->tm_mday, currentPrint->tm_hour,
currentPrint->tm_min, currentPrint->tm_sec);
                       if (num_blobs>0){
                                fprintf(pFile, "%d%02d%02d %02d%02d%02d ",
currentPrint->tm_year+1900, currentPrint->tm_mon+1,
                                currentPrint->tm_mday, currentPrint->tm_hour,
currentPrint->tm_min, currentPrint->tm_sec);
                                int num_brightestBlobs=blobBrightest.GetNumBlobs();
                                cout<<"we are writing blobs!!!\n";
                                for(int l=0;l<num_brightestBlobs;l++){
                                       currentBlob=blobBrightest.GetBlob(l);
                                       CvPoint currentBlobCentre;
                                           double mm00 = currentBlob->Moment(0, 0);
                                           double mm10 = currentBlob->Moment(1, 0);
                                           double mm01 = currentBlob->Moment(0, 1);
                                           currentBlobCentre.x = (int) mm10/mm00;
// calculate the x,y centre of motion
                                           currentBlobCentre.y = (int) mm01/mm00;
                                       fprintf( pFile, "x%d=%03d y%d=%03d
",l,currentBlobCentre.x,l,currentBlobCentre.y);
                                }
                                fprintf( pFile,"\n");
                       }
                       //fprintf( pFile,"\n");
                       lastSavedTime = currentTime;
                }


        switch (cvWaitKey(1)) {
            case 27:
                running = false;
                break;
        }
        cvReleaseImage(&depthImage); cvReleaseImage(&depthImageMask);
        cvReleaseImage(&colourImage); cvReleaseImage(&depthImageVisible);
              //set running time=48 hours
              if(currentTime-startTime>172800)
                     break;
    }
    fclose (pFile);
    return 0;
}
```

```
//Create a mask of valid depth values
IplImage *createDepthMask(IplImage *depthImage) {
    IplImage *depthImageMask = cvCreateImage(cvGetSize(depthImage), IPL_DEPTH_8U, 1);
       cvSetZero(depthImageMask);
    //Loop through each pixel in the depth image, if the depth value isn't 0, set the
corresponding pixel in the mask to 255
    for (int y=0; y<depthImage->height;y++) for (int x=0; x<depthImage->width; x++)
        if (CV_IMAGE_ELEM(depthImage, unsigned short, y, x)!=0)
CV_IMAGE_ELEM(depthImageMask, unsigned char, y, x)=255;
    return depthImageMask;
}

double getBlobDistance(CBlob *blob1,CBlob *blob2) {
    double distance;
       CvPoint centre1, centre2;
       //calculate centre of blob1
       double m00 = blob1->Moment(0, 0);
       double m10 = blob1->Moment(1, 0);
       double m01 = blob1->Moment(0, 1);
       centre1.x = (int) m10/m00;
       centre1.y = (int) m01/m00;
       //calculate centre of blob2
       double n00 = blob2->Moment(0, 0);
       double n10 = blob2->Moment(1, 0);
       double n01 = blob2->Moment(0, 1);
       centre2.x = (int) n10/n00;
       centre2.y = (int) n01/n00;
       //calculate the distance of two blobs
       distance=sqrt(pow (double(centre2.x-centre1.x),2)+pow (double(centre2.y-
centre1.y),2));
    return distance;
}
```

Appendix 5.1: Locality Authorisation form for CDHB

29.05.14. To Hamish, for your signature, pls. thank you. Heidi RDA 14083

4.6.14 - To Pauline, for your approval pls Thank you. Heidi

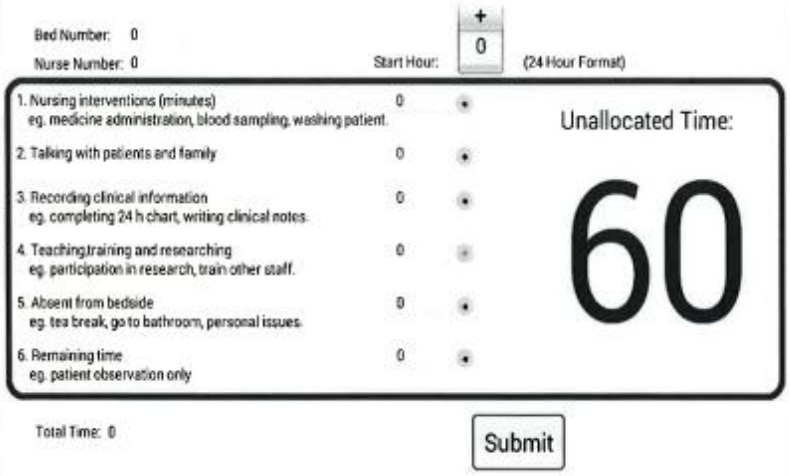
Locality Authorisation for Canterbury District Health Board

[Please return documentation to CDHB Research Office, (03) 364 3630, 36 Cashel St, Christchurch]

Locality authorisation is a standard condition of HDEC approval for the conduct of a study at a given locality. Locality review is the process by which a locality assesses its suitability for the safe and effective conduct of a study.

Note: Not required HDEC Review and TKW Maori Consultation. No cost implications to the DHB as indicated in Geoff Shaw's email of 19.05.14.

Part one: General

Project title:	A Novel Clinical Resource Matching System
Locality to be assessed:	ICU, Christchurch Hospital
Brief outline of study:	This research, will evaluate a novel system to measure clinical activity at patient bedside using a motion sensing device. This system provides the ability to assess clinical activity (anonymously) at the bedside continuously without the use of manual labour; thus enabling to quantitative measurement of usual clinical activities. An infrared depth sensing method is will be implemented, using two *Microsoft Kinects* devices. These are motion sensing devices with an embedded camera and infrared sensor. Cables will run from these devices to two portable (laptop) computers. The sensors will detect the presence of clinical staff on either side, or at the foot of the bed. The sensors 'see' a cross-section of a person as a grey blob. This is deliberate to avoid identifying individuals. The sensors are 'blind' to the bed area, thus will not convey any patient images. This tool is solely designed to assess clinical staff activity at the patient's bedside. Staff will not be required to wear special sensors, nor will any identifying data be used. The ICU staff, after undergoing a brief teaching session about the study, will be asked to complete an assessment of how they spent the last hour caring for their patient. Specifically staff will be asked to record the time spent relating to the following categories of work. See figure below.  The two Kinect sensors will be attached to the ceiling above "Bed 7" using (strong) neodymium magnets, which attach to a small metal plate adhered to the ceiling using double-sided sticking tape. This study is a proof-of concept study as part of a study by a doctoral student (Peng Guo)

CDHB Locality Authorisation Form June 2012 1

Local Principal investigator:	Dr Geoffrey M Shaw
Contact person & contact details:	Dr Geoffrey M Shaw Intensive Care +64 21 619 686 or +63 3 364 1077 Geoff.Shaw@cdhb.health.nz
Other local investigators:	Peng Guo Distinguished Professor J Geoffrey Chase, University of Canterbury

Part two: Locality Issues

1)	**Suitability of local researcher** Is the investigator(s) at the locality suitably qualified, experienced, registered and indemnified to take professional responsibility for the conduct of the study at the locality?	☒ Yes	☐ No
2)	**Suitability of the local research environment** Are all the resources and/ or facilities that the study requires appropriate and available?	☒ Yes	☐ No
	Would conducting the study at the locality impact on the provision of publicly funded health care at that locality?	☐ Yes	☒ No
	Have all potentially affected managers of resources such as patient records or laboratory managers been notified?	☒ Yes	☐ No
3)	Have issues such as **cultural issues** specific to this locality or to people being recruited at this locality been addressed?	☒ Yes	☐ No

Documents Attached:

- Email from Eru Waiti, TKW chair, dated 21.05.14 - no Maori Consultation Required
- Email from Ethics dated 14.11.13 re "out-of-scope" of HDEC review
- Email from Geoff Shaw dated 19.05.14 - re no funding required as there is no cost involved to the DHB.

SIGN OFF

I hereby confirm that all information within this application is true and correct and I will ensure all consents and approvals are obtained and sighted by the Research Office before research commences:

Principal Investigator:	Dr Geoffrey M Shaw Name	..... Signature	19th May 2014 Date

Recommendations: *I hereby endorse this application to undertake this research on behalf of the CDHB and guarantee the availability of facilities, equipment, and any special support which may be required as detailed in the application. I confirm that it is in accordance with current CDHB policy.*

Service Manager:	Ms Lesley Owens Name	..... Signature	28.5.14 Date
Clinical Director:	Dr Seton J Henderson Name	..... Signature	14/5/14 Date

Comments from Signatories: *(Optional)*

Research Office Use Only:

Finance Office:	Harue Akimoto Management Accountant Christchurch Hospital Campus Finance Name	..... Signature	3/06/14 Date

I am satisfied that suitable arrangements have been made for the safe and effective conduct of this study and therefore this study is authorised to be conducted within the CDHB

General Manager:	Ms Pauline Clark Name	..... Signature	05/06/14 Date

Appendix 5.2: Approval of Kinect and power supply socket installation

Canterbury
District Health Board
Te Poari Hauora ō Waitaha

Office of the
MAINTENANCE & ENGINEERING DEPT
CHRISTCHURCH HOSPITAL
PO Box 1600 Tel (03) 364-0220
CHRISTCHURCH Fax (03) 364-0224

MEMORANDUM

27th June 2014

TO: Nghia Pham, Technician, Clinical Engineering

FROM: Graeme Coulson, Supervisor Maintenance Services

SUBJECT: INSTALL ADDITIONAL SOCKET OUTLET FOR INFRARED CAMERA

Please find below our quotation for installing an additional socket outlet for infrared camera:

Price $483.00 + GST

Scope of Work

- Arrange access to area.
- Isolate existing circuit supplying bollard.
- Install new socket outlet including.
- Install required equipotential earthing to new socket outlet
- Test as per 3003:2011
- Inspect as per 300:2011
- Test label and provide CeSC

Should you require further information, please do not hesitate to contact the undersigned.

Regards

Graeme Coulson
Christchurch Hospital
Site Maintenance Manager (Engineering)

Appendix 6.1 Nursing activity observation form

Appendix 7.1: APACHE-III scoring system

TABLE 1a

APACHE III scoring system, comprised of the sum of three components: an acute physiology score, an age score, and a chronic health problems score. Scores range from 0 to 299 (physiology,0 to 252; chronic health evaluation,0 to 23; age,0 to 24),with higher values representing a worse prognosis.

Pulse	8 ≤ 39	5 40-49	0 50-99	1 100-109	5 110-119	7 120-139	13 140-154	17 ≥ 155	
Mean BP (mmHg)	23 ≤ 39	15 40-59	7 60-69	6 70-79	0 80-99	4 100-119	7 120-129	9 130-139	10 ≥ 140
Temperature (°C)	20 ≤ 32.9	16 33-33.4	13 33.5-33.9	8 34-34.9	2 35-35.9	0 36-36.9	4 ≥ 40		
Respiratory Rate	17 ≤ 5	8 6-11	7 12-13	0 14-24	6 25-34	9 35-39	11 40-49	18 ≥ 50	
PaO_2* (mmHg)	15 ≤ 49	5 50-69	2 70-79	0 ≥80					
$AaDO_2$** (mmHg)	0 < 100	7 100-249	9 250-349	11 350-499	14 ≥ 500				
Hematocrit (%)	3 ≤ 40.9	0 41-49	3 ≥ 50						
WBC Count (cu/mm) x 1000	19 < 1.0	5 1.0-2.9	0 3.0-19.9	1 20-24.9	5 ≥ 25				
Serum Creatinine† (mg/dl) without ARF	3 ≤ 0.4	0 0.5-1.4	4 1.5-1.94	7 ≥ 1.95					
Serum Creatinine (mg/dl) with ARF	0 0-1.4	10 ≥1.5							
Urine Output (cc/day)	15 ≤ 399	8 400-599	7 600-899	5 900-1499	4 1500-1999	0 2000-3999	1 ≥ 4000		
Serum BUN (mg/dl)	0 ≤ 16.9	2 17-19	7 20-39	11 40-79	12 ≥ 80				
Serum Na^+ (mEq/L)	3 ≤ 119	2 120-134	0 135-154	4 ≥ 155					
Serum Albumin (g/dl)	11 ≤ 1.9	6 2.0-2.4	0 2.5-4.4	4 ≥ 4.5					
Serum Bilirubin (mg/dl)	0 ≤ 1.9	5 2.0-2.9	6 3.0-4.9	8 5.0-7.9	16 ≥ 8.0				
Serum Glucose (mg/dl)	8 ≤ 39	9 40-59	0 60-199	3 200-349	5 ≥ 350				
Age	0 ≤ 44	5 45-59	11 60-64	13 65-69	16 70-74	17 75-84	24 ≥ 85		
Comorbidities	• AIDS 23	• Hepatic Failure 16	• Lymphoma 13	• Metastatic Cancer 11	• Leukemia/Multiple Myeloma 10	• Immune Compromised 10	• Cirrhosis 4		

TABLE 1b

APACHE III acute physiology scoring for neurologic abnormalities.

Motor (Verbal) see ‡	Oriented, Converses	Confused Conversation	Inappropriate Words & Incomprehensible Sounds	No Response
Obeys verbal command	0 / NA	3 / NA	10 / NA	15 / 16
Localizes pain	3 / NA	8 / NA	13 / NA	15 / 16
Flexion withdrawal/decorticate rigidity	3 / NA	13 / NA	24 / 24	24 / 33
Decerebrate rigidity/no response	3 / NA	13 / NA	29 / 29	29 / 48

TABLE 1c

APACHE III acute physiology scoring for acid-base disturbances.

Acute Physiology	pCO_2 < 25	25 to < 30	30 to < 35	35 to < 40	40 to < 45	45 to < 50	50 to < 55	55 to < 60	pCO_2 ≥ 65
pH < 7.15				12					4
7.15 to < 7.20									
7.20 to < 7.25			9			6	3		2
7.25 to < 7.30									
7.30 to < 7.35						0			1
7.35 to < 7.40			5						
7.40 to < 7.45									
7.45 to <7.50						0	2		
7.50 to < 7.55									
7.55 to < 7.60			3				12		
7.60 to < 7.65									
pH ≥ 7.65	0								

APACHE III

was introduced to address some of the flaws of APACHE II. Although APACHE III resembles APACHE II, it includes new variables such as prior treatment location and the disease requiring ICU admission. In APACHE III scoring, the patient's age and chronic health history are worth up to 47 points. Within 24 hours of ICU admission, 17 physiologic variables are measured and may add up to a maximum of an additional 252 points. The resulting total score, in combination with prior treatment location and principal ICU diagnosis provides a predicted mortality. .

BENEFITS OF APACHE III:

- Saves lives by better managing the care of critically ill individuals
- Reduces frequency of complications
- Evaluates and improves ICU performance
- Optimizes ICU resource allocation

TABLE 1a SCORE		a
TABLE 1b SCORE	+	b
TABLE 1c SCORE	+	c
APACHE III SCORE	=	a+b+c

‡ Scoring for: Eyes open / do not open spontaneously or to painful/verbal stimulation
NA = Not applicable
*If FiO_2 is ≤50%, record $AaDO_2$; ** Alveolo-arterial Oxygen Difference: If FiO_2 is <50%, record PaO_2;
†Acute renal failure (ARF) is defined as creatinine ≥ 1.5 mg/day and urine output < 410 cc/day and no chronic dialysis.

References. 1. Knaus WA et al. Chest 1991; 100(6): 1619-36. 2. Yung-Chang C et al. Renal Failure 2002; 24(3): 285-96.

Appendix 7.2: Most commonly used unit conversion:

Agent	Conventional Unit	Conversion Factor	SI Unit
Albumin	g/dL	10	g/L
Bilirubin	mg/dL	17.1	µmol/L
Creatinine	mg/dL	88.4	µmol/L
Glucose	mg/dL	0.0555	mmol/L
Hematocrit	%	0.01	Proportion of 1.0
Platelets (thrombocytes)	x 103/µL	1	x 109/L
Potassium	mEq/L	1	mmoI/L
Sodium	mEq/L	1	mmol/L
Urea nitrogen	mg/dL	0.357	mmol/L
White blood cell count	x 103/µL	1	x 109/L

Appendix 7.3: Daily collected physiology items, definitions, ranges, and unit

	Item	Definition and function	Absolute Range	Normal Range	Unit	Where to locate
1	24 hour Urine Output	Total urine output measured in ml in the first 24 hours of the ICU admission.	0-30000	2000-3999	cc/day	24-h chart
2	Age	The length of time, measured in calendar years, between a patient's birth and their admission to ICU	16-105	16-44		24-h chart
3	Albumin	Albumin is a family of globular proteins found in many plant and animal tissues that tend to bind a wide variety of ligands. Albumin is the main protein in blood plasma. Low serum levels occur in conditions associated with malnutrition, inflammation and liver and kidney diseases.	5~65	25-44	g/dl	Biochemistry report
4	Bilirubin	Bilirubin is a dark orange, yellow pigment that is a breakdown product of hæmoglobin; it is conjugated in the liver and extreted in the bile. The abnormal buildup of bilirubin causes jaundice. Total and direct bilirubin are usually measured for or to monitor liver or gallbladder dysfunction.	0-1200	0-51	mg/dl	
5	Blood Pressure (Systolic /Diastolic)	Systolic Blood Pressure: The blood pressure during the contraction of the left ventricle of the heart. Diastolic Blood Pressure: The blood pressure after the contraction of the heart while the chambers of the heart refill with blood.	65-250 (Systolic) / 0-180 (Diastolic)		mmHg	Biochemistry report
6	Creatinine	The breakdown product of creatine, a constituent of muscle tissue, that is excreted by the kidney and whose serum level is used to evaluate kidney function.	5~2000	132-171.5 (if Urine > 410mL) 5-132 (if Urine ≤ 410mL)	mg/dl	24-h chart
7	FiO_2	Fraction of Inspired Oxygen: The amount of oxygen taken up by arterial blood and expressed as a percentage of total oxygen of inspired air.	21 (room air) - 100		%	Biochemistry report
8	Glucose	A simple sugar monosaccharide having two isoforms, alpha and beta, with a chemical structure of C6H12O6 that acts as an energy source for both plants and animals by reacting with oxygen, generating carbon dioxide and water, and releasing energy.	0-90	3.3-11.1	mg/dl	24-h chart
9	Hæmoglobin	The red respiratory protein of erythrocytes, consisting of approximately 3.8% hæme and 96.2% globin (64.5 KD), which as oxyhæmoglobin (HbO2) transports oxygen from the lungs to the tissues where the oxygen is readily released and HbO2 becomes Hb	1~25	13.7-16.7	mg/dl	Admission form
10	HCO_3	Bicarbonate: Bicarbonate is alkaline, and is vital in maintaining acid-base homeostasis.	2~50	20-50	mEq/L	24-h chart
11	Hct	Hæmatocrit: A measure of the volume of red blood cells expressed as a percentage of the total blood volume.			%	Biochemistry report
12	Heart Rate	The number of heartbeats per unit of time, usually expressed as beats per minute. The heart rate is the ventricular rate as shown on an ECG trace - not the pulse rate.	0-180	51-100		Blood count report
13	K	Potassium: An element with atomic symbol K, atomic number 19, and atomic weight 39.10. This metallic element is important in body functions such as regulation of blood pressure and of water content in cells, transmission of nerve impulses, digestion, muscle contraction, and heartbeat.	0.05-12	3.5-5.4	mmol/L	Blood gaese report
14	MAP	Mean Arterial Pressure: The mean pressure of the blood within the arterial circulation. The arterial pressure may be directly measured by insertion of an intra-arterial catheter connected to a transducer. The mean arterial pressure	20-200	80-99	mmHg	Blood count report

		(MAP) can be calculated by subsequent analysis of the waveform. MAP can be approximated without an invasive procedure using the following formula: diastolic pressure plus 1/3 of the pulse pressure, where pulse pressure is systolic pressure - diastolic pressure. This value is automatically calculated based on the values entered for systolic and diastolic blood pressure, but may be entered manually.				
15	Na	Sodium: An element with atomic symbol Na, atomic number 11, and atomic weight 23. This mineral is needed by the body to keep body fluids in balance. Sodium is found in table salt and in many processed foods. Too much sodium can cause the body to retain water.	100-215	135-154	mmol/L	24-h chart
16	paO_2	Partial Pressure of Oxygen: A measurement of the pressure of oxygen dissolved in the blood and how well oxygen is able to move from the airspace of the lungs into the blood. It is lower than normal in patients with asthma, obstructive lung disease, or certain blood diseases and in healthy individuals during vigorous exercise. Reported in millimetres of mercury (mmHg)	15-750		mmHg	Biochemistry report
17	pCO_2	Partial Pressure of Carbon Dioxide. The part of total blood gas pressure exerted by carbon dioxide. This pressure decreases during heavy exercise, rapid breathing, or in association with severe diarrhea, uncontrolled diabetes, or diseases of the liver or kidneys. It increases with chest injuries or respiratory disorders. Reported in millimetres of mercury (mmHg)	5-300		mmHg	MAP = [(2 x diastolic)+systolic] / 3
18	pH	Potential of Hydrogen A measurement of the acidity or alkalinity of a fluid on a scale of 0 to 14, calculated as the logarithm of the reciprocal hydrogen-ion concentration in gram atoms per litre	6.5-8			Biochemistry report
19	Platelets	Platelets are a component of blood whose function (along with the coagulation factors) is to stop bleeding by clumping and clogging blood vessel injuries.		150-400	10^9/L	Blood gaese report
20	Respiratory Rate	The rate of breathing (inhalation and exhalation) measured within a unit time, usually expressed as breaths per minute. For a non ventilated patient the respiratory rate is the number of unassisted breaths per minute. If the patient suffers a cardiorespiratory arrest or death in the first 24 hours, the values recorded should be the lowest measured values prior to arrest or death. It is inappropriate to record variable as zero merely because cardiorespiratory arrest or death has occurred. Where an automated monitoring system is being employed then values on the preceeding hour pre-arrest should be considered in the selection of the worst value. e.g. if arrest at 11:35 am consider values for 11:00	0-80	15-25 (if not ventilated) 6-15 (if ventilated).		Blood gaese report
21	Temperature	The measurement of a patient's core temperature. Core temperature sites include oral, tympanic, nasopharyngeal, rectal, oesophageal, pulmonary artery and bladder.	25-46	36-39.9	℃	Blood gaese report
22	Urea	A nitrogenous compound containing a carbonyl group attached to two amine groups with osmotic diuretic activity. It is formed in the liver from ammonia produced by the deamination of amino acids, and is the principal end product of protein catabolism and constitutes about one half of the total urinary solids.	1-100	1~9	cc/day	Biochemistry report

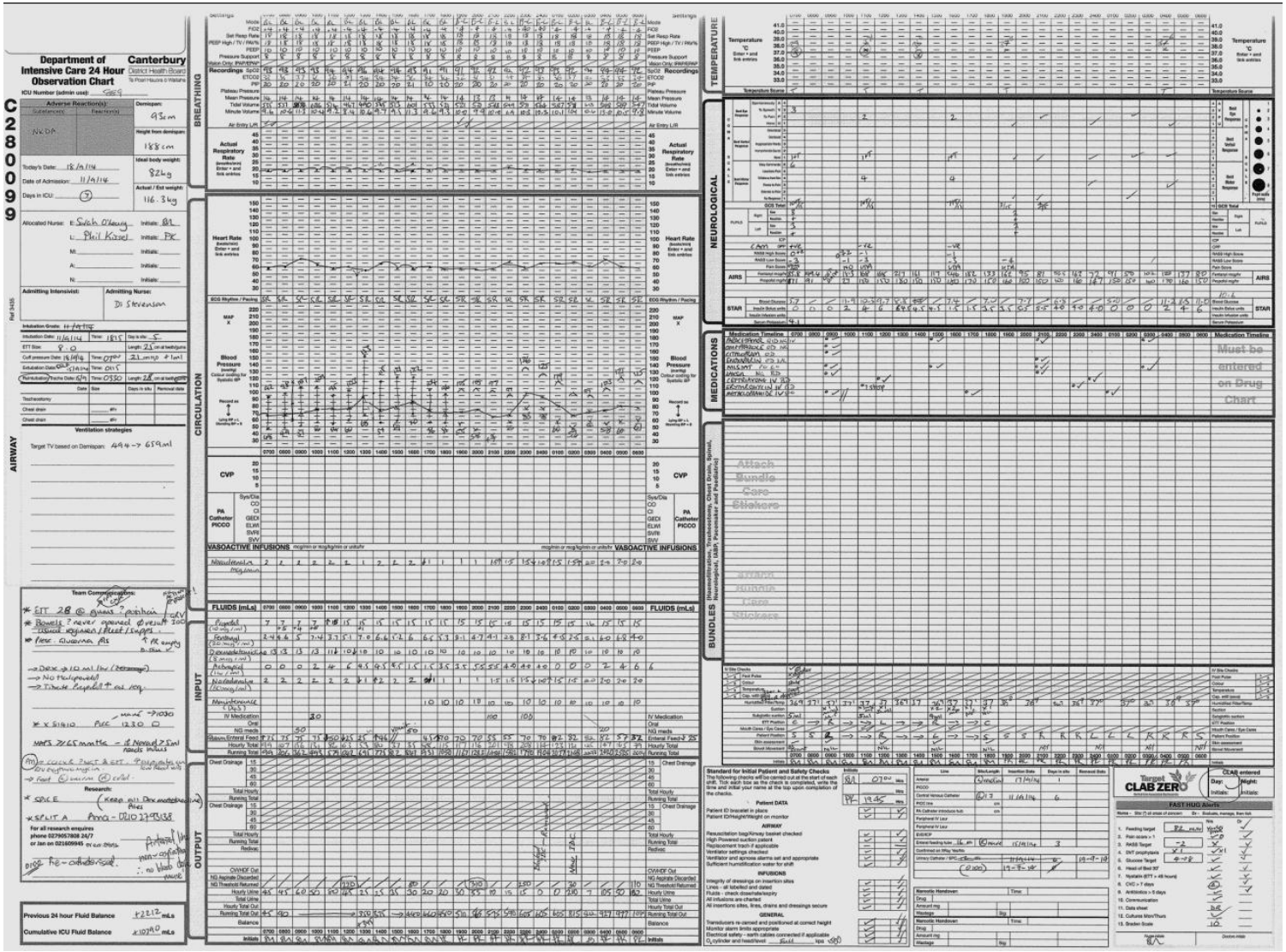
Appendix 7.4: TISS-28 items, what is each item stand for, where to locate these items, and calculation.

TISS-28 items and where to find this information in ICU

No.	TISS-28	What is this item for?	Where is this info recorded?	Points
Basic Activities				
1	Standard monitoring. Hourly vital signs, regular registration and calculation of fluid balance.	Basic monitoring, including Blood Pressure, Heart Rate, FiO_2% and CO_2%	From the patient chart, if it has heart rate and blood pressure, 5 points From the monitor	5
2	Laboratory. Biochemical and microbiological investigations.	This is investigation of blood sample. Every 5-6 hours, patient blood sample is tested.	It's all on radiometer ABL 90 (arterial blood line) report. If we have blood gas data.	1
3	Single Medication, any route (IV, PO, IM, etc.).	Drugs: Vasoactive: such as Nor adrenaline, Vasopressin Fluids: such as propofol, spilit B, Maint D4S.	1. Patient chart-Input (exclude vasoactive drugs) 2. Medications: such as Enoxaparin 40mg. 3. patient medication record file	2
4	Multiple intravenous medications (more than 1 drug, single shots, or continuously)	See Item 3.	See Item 3.	3
5	Routine dressing changes. Care and prevention of decubitus and daily dressing change)	Only for patients with wounds. Once per 3-5 days.	Nurse note or dressing note.	1
6	Frequent dressing changes (at least one time per each nursing shift) and /or extensive wound care	See Item 5.	See Item 5.	1
7	Care of drains. All (except gastric tube)	Nurse clean urine drain and gastric drain	Patient chart-Output-Hourly Urine and Total Urine	3
Cardiovascular Support				
8	Single vasoactive medication. Any vasoactive drug.	Stimulate patient's circulation	Patient chart-vasoactive infusion Or Fluid	3
9	Multiple vasoactive medications. More than 1 vasoactive drug, disregard type and dose.	See Item 8.	See Item 8.	4
10	Intravenous replacement of large fluid losses. Fluid replacement >3 liters per square meter per day, disregard type of fluid administered.	If patient loss huge amount of fluid.	Patient chart-Input, such as Maint D4S, 80ml/h*24=1.9L<3L	4
11	Peripheral arterial catheter	On patient left arm. Test their blood pressure and take blood sample.	Line: Arterial . Normally if patient have radiometer ABL 90. They have this item.	5
12	Left atrium monitoring. Pulmonary artery floatation catheter with or without cardiac output measurement.	Normally only cardio ICU patient require this. Measure volume of 1 circulation.	Circulation-CVP (central venous pressure) Normally CICU has this.	8
13	Central venous line	On patient neck. Intravenous fluid and drugs. Most patients have this item.	Line: Central Venous Line, Also, Check 'Input-Fluid'.	2
14	Cardiopulmonary resuscitation after arrest in the last 24 hours (single precordial percussion is not included)	CPR. Chest press to rescue patient.	It is recorded on CPR form (cardiopulmonary resuscitation). If not, it is recorded on Blood Pressure or Heart Rate	3
Specific Interventions				

15	Single specific interventions in the ICU. Naso or orotracheal intubation, introduction of a pacemaker, cardioversion, endoscopies, emergency surgery in the past 24 hours, gastric lavage.	Naso or orotracheal intubation is for ventilator or food. Pacemaker is normally for cardio ICU, to make heart rate normal. Cardioversion is 2 patches, to bring heart rhythm normal. Endoscopies is check image inside. Gastric lavage is empty stomach.	Intubation is recorded in Airway, intubation date. Also check Enteral Feed. Pacemaker is normally happened in cardio ICU, check CVP. Cardioversion, check heart rate. Endoscopies and surgery, check 'Team Communication', gastric lavage is never used in CHCH ICU.	3
16	Multiple specific interventions in the ICU. More than one, as described above.	See item 15.	See item 15.	5
17	Specific interventions out of ICU. Surgery or diagnostic procedures.	See item 15.	Check 'Team Communication' and patient file.	5
Ventilatory Support				
18	Mechanical Ventilation. (Any form of ventilation or assisted ventilation with or without PEEP; with or without muscle relaxants; spontaneous breathing with PEEP	Help patient easily breath	Check 'Breathing' Setting Mode.	5
19	Supplementary ventilator support	Other form of ventilation support	Not happen in CHCH ICU	2
20	Care of artificial airways. Endotracheal tube or tracheostoma		IV site check-suction.	1
21	Treatment for improving lung function. Thorax physiotherapy, incentive spirometry, inhalation therapy, intratracheal suction.	Thorax physiotherapy is from physio, incentive spirometry is not in ICU. Inhalation therapy is for asthma. Intratracheal suction is caring patient.	Check 'Team communication' for physiotherapy, and 'medication' for asthma Normally not happen	1
Renal Support				
22	Hemofiltration techniques. Dialytic techniques.	For dialysis patient	Check sticker in 'Bundles'	3
23	Quantitative urine output measurement.		'Output', hourly urine and total urine. Almost every patient has this.	2
24	Active diuresis (eg. Furosemid >0.5mg/kg/day for overload.)	Treatment of ethma. Urine a lot	Patient chart, medicines, Medication check whether has Furosemide	3
Neurologic Support				
25	Measurement of intracranial pressure (ICP)	Measure skull pressure	Patient chart, Check ICP in 'Neurological'. Normally for head wound patients	4
Metabolic Support				
26	Treatment of complicated metabolic acidosis/ alkalosis	Acidosis is an increased acidity in the blood and other body tissue	Blood gases, Check PH value. Increase CO_2 to increase breath rate. If PH changes a lot, it is needed.	4
27	Intravenous hyperalimentation	Consume more food than appropriate.	Check patient chart, medicine, whether it has TPN.	3
28	Enteral feeding. Through gastric tube or other GI route (eg. jejunostomy)	Feed food	Patient chart, Enteral Feed in 'Input'	2

Appendix 7.5: 24-hour patient chart:



Appendix 10.1: Distribution of time per nursing activity in relation to work shifts

	Categories of Nursing Activities[a]							
Shift	1	2	3	4	5	6	Total[b]	Accuracy
Morning	40.0	14.8	21.3	4 6	17.8	1.6	43.0	050
Evening	51.1	11.9	20.2	1.8	13.1	2378 1.9	32.9	.047
Night	38.3	11.1	23 4	3.3	21.5	1821 2.4	24 1	069
Total	43.3	12.9	21.4	3.3	17.1	1331 1.9	100	.031
Sign column	2392 .000	716 .004	1186 .147	185 .000	947 000	104 .229	5530 .000	

[a]Category 1, activities involving patient care as scored in Therapeutic Intervention Scoring System (TISS), category 2, activities involving patient care not scored in TISS; category 3, "indirect" patient care; category 4, organizational tasks; category 5, work breaks, category 6, other activities (see Table 5); sign column, overall significance per column; [b]total per category. The first figure indicates overall percentage of time per category. The second figure is the total number of "work sampling" registrations made in the category.

Per nursing activity category in each shift, time is expressed as a percentage of a mean of 490 mins per nurse shift.